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TESIS DOCTORAL

Economic effects of a high share of renewable energies on power systems

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por transmitirme
la importancia de la educación
a la que no tuvieron acceso.

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Resumen

El objetivo de esta tesis es el estudio de la participación de las energías renovables en el sistema eléctrico español. Para ello, se han desarrollado dos tipos de estudios en este trabajo. Por un lado, el objetivo de la primera parte es la evaluación de la participación de los productores eólicos en el mercado eléctrico. Por otro lado, se estudiarán los efectos que se producen en el sistema eléctrico al incrementar la potencia renovable instalada.

Debido a la naturaleza intermitente del viento y a su parcial predictibilidad, la participación de productores eólicos en el mercado de electricidad supone desvíos con respecto a la programación inicial, que implican costes. Utilizando herramientas de predicción eólica a corto plazo estas pérdidas pueden reducirse y, si el mercado permite actualizar las ofertas de potencia en los mercados intradiarios, los ingresos del productor eólico pueden incrementarse en un porcentaje significativo.

Las pérdidas debidas a los desvíos de un productor eólico son importantes, y pueden ser reducidas mediante el uso de ofertas estratégicas. Para ello, en este estudio se emplea una herramienta que maximiza los ingresos de los productores eólicos en los mercados de electricidad. Mediante un proceso estocástico, se ha diseñado un algoritmo para la realización de ofertas estratégicas al mercado que tiene en cuenta las variables involucradas en el proceso, tales como predicción de la potencia eólica, y los precios de los mercados diario, intradiarios y de desvíos. Ya que el valor de estas variables no se conoce de antemano, se usa un programa de predicción de potencia eólica a corto plazo, que proporciona las variables de entrada para la herramienta de ofertas estratégicas. Además se han integrado módulos de predicción de los precios del mercado intradiario y de los desvíos en el proceso de optimización. El problema considerado determina la potencia óptima a ofertar en el mercado intradiario teniendo en cuenta la potencia ofertada previamente al mercado diario y considerando la incertidumbre de las variables aleatorias del problema. Se incluye también un análisis de riesgos que estudia los efectos en el sistema eléctrico de que los productores eólicos adopten estrategias de participación.

Partiendo de datos históricos de producción eólica y predicciones se ha implementado un algoritmo que puede funcionar en tiempo real, obteniéndose, por tanto, resultados realistas. Las simulaciones se han realizado durante 10 meses en 2007 y 2010, proporcionando un análisis robusto de las diferentes estrategias aplicadas. Como consecuencia, este análisis contribuirá a la extracción de valiosas conclusiones con respecto a la participación de los productores eólicos en el mercado de electricidad español.

El aumento de la capacidad de energía instalada procedente de fuentes renovables ha cambiado tanto el funcionamiento del sistema eléctrico como la operación de las centrales convencionales. Con respecto al último aspecto, las centrales eléctricas que usan combustibles fósiles han cambiado su modo de operación para adaptarse a la variabilidad y parcial predictabilidad de las fuentes de energía renovables. Este hecho incrementa los costes de operación de las centrales convencionales. Además, los precios del mercado eléctrico experimentarán cambios ante un incremento de la capacidad renovable, tales como la disminución de su precio medio y el aumento de su variabilidad. Adicionalmente, en países con un abundante recurso solar, es necesario estudiar los efectos de un aumento de la capacidad de energías renovable instaladas en el sistema eléctrico, que incluya una alta proporción de energía fotovoltaica y termoeléctrica en el mix de generación. Por tanto, se ha desarrollado un modelado de la tecnología termoeléctrica de concentración en este trabajo. Para analizar el impacto de la configuración futura del mix de generación en el sistema eléctrico se ha utilizado un modelo de programación horaria. Se ha incluido tanto las características como la potencia instalada de las centrales que utilizan combustibles fósiles, así como la estimación de las series futuras de producción de energías renovables. La discusión de resultados contiene un análisis de algunas características relevantes del comportamiento del sistema eléctrico futuro, tales como, precios del mercado diario, producción anual por tecnología, factores de capacidad de las distintas tecnologías, energía eólica vertida, ratio de cobertura de la demanda procedente de fuentes renovables, variación horaria de la energía suministrada por centrales hidráulicas convencionales, carbón y gas natural, emisiones de gases de efecto invernadero y costes de operación.

Abstract

The aim of this thesis is to study the participation of renewable energies in the Spanish power system. For this purpose, two kind of studies have been developed in the present work. On the one hand, the first part of the work aims to assess the participation of wind energy producers in the Spanish electricity market. On the other hand, the overall effects of an increased installed capacity of renewable energies on the power system are evaluated.

Due to the intermittent nature and the low predictability of wind power, the participation of this energy in the day-ahead market implies large deviations from the initial schedule, which leads to a cost that has to be borne by the wind farm owner. By means of short term wind power prediction programs, these losses may be reduced, and, if the market allows the possibility of updating previous bids at intraday markets, the total income of the wind power producers can be increased by a significant percent.

The imbalance losses for a wind power producer are important, and may be reduced by strategic bidding. Then, a tool that maximizes the incomes of wind power producers in electricity markets is employed in this study. Through a stochastic process a strategic bidding algorithm is designed, which takes into account the variables involved in the process, namely wind power forecasts, daily, intraday and imbalance market prices. As these variables are not known in advance, their forecasts are necessary as input data of the strategic bidding tool. So, prediction tools are integrated in the optimization process, which forecast intraday and imbalance prices. Also a short-term wind power prediction program is included in the tool. The problem considered is the optimization of the bid to the Intraday Market, given a position in the Daily Market, and considering the uncertainties of the involved random variables. Moreover, a risk analysis is included in the results to study the effect of several risk attitudes in both the incomes obtained by wind power producers and the errors incurred by them.

Realistic results coming from both historical real data of production and forecasts, and a real-time simulation project will be presented in this work. Simulation results were evaluated for ten months in 2007 and 2010, leading to a thorough analysis of the different strategies applied. In consequence, this analysis will contribute to extract valuable conclusions with regard to the participation of wind energy producers in the Spanish electricity market.

The increased share of renewable energies has changed both power system functioning and conventional plants operation. With regard to the latter, power plants using fuel have change their operation mode to accommodate to the variability and partial predictability of renewable energy sources. This fact increases the operation costs of the conventional plants. Besides, market prices behaviour will experience changes, such as the decrease of average prices and the increase of their variability. The positive effects of an increased renewable installed capacity are also assessed. Furthermore, in countries with abundant solar resource, studying the effects of a higher share of renewable energy sources on the generation mix is necessary, including a high portion of photovoltaic and solar thermal energy in the generation portfolio. Therefore, a model of the concentrated solar power generators has been developed in this work. The results of the thermoelectric model supplies the annual production of this technology, which has been integrated in the generation schedule model. To analyse the impact of the future configuration of the generation mix on the power system, a model of unit commitment has been employed. It includes the characteristics and installed capacity of the generators using fuel and the estimation of the future production series of renewable energies. The results discussion contains an analysis of some relevant characteristics of the future power system behaviour, such as, daily market prices, yearly production by technology, capacity factors of the different technologies, wind spilled energy, ratio of demand coverage coming from renewable sources, hourly variation of the energy supplied by hydro, coal, and natural gas power plants, greenhouse emissions and operation costs.

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Nomenclature

α^{est}	Represents the average value of the imbalance prices ratio α_t^{sell} and α_t^{buy} in the year 2007.
α^{known}	Real values of the imbalance prices ratio.
α_t^{down}	Ratio of the imbalance price for a negative energy deviation, i.e., short deviations.
α_t^{up}	Ratio of the imbalance price for a positive energy deviation, i.e., long deviations.
α_k	Bin value of imbalance price, corresponding to the $k-th$ alpha bin. [€]
α_t^{buy}	Quotient of imbalance price for short deviations at hour t.
α_t^{sell}	Quotient of imbalance price for long deviations at hour t.
β	Confidence interval of the distribution function.
$\beta_{m,i}$	m parameter of the ID prices prediction time-series model, related to the previous sessions of the intraday market prices and the daily market price at this hour t.
ΔAPE	Relative difference between $APE_{proposed}$ and $APE_{standard}$. [MW]
ΔP	Average power error. [MW]
δ	Declination angle. [º]
$\dot{W}_{des}$	Power output in the turbine at design point. [MW]

η_{col} Overall efficiency of the collectors.

$\eta_{cycle,des}$ Efficiency of the turbine at the design point.

γ_{col} Colector azimuth angle. [º]

γ_s Solar azimuth. [º]

ω Threshold of CVaR, that is, the minimum value for the revenues forecasted in the bidding strategy. [€]

ω_h Hourly angle of the location. [º]

$\overline{R}$ Expected revenue for the wind farm participation. [€]

$\phi_{l,i}$ l parameter of the ID prices prediction time-series model, regarding to the intraday market price in session i, with a k hours horizon.

π_t^{down} Imbalance price for a negative energy deviation, i.e., short deviations. [€/MWh]

π_t^{up} Imbalance price for a positive energy deviation, i.e., long deviations. [€/MWh]

$\pi_{d,t}$ Daily market price at hour t. [€/MWh]

$\pi_{i,t}$ Intraday market price for intraday market i at hour t. [€/MWh]

π_s Occurrence probability of scenario s.

π_t^{buy} Imbalance price for short deviations at hour t. [€/MWh]

π_t^{sell} Imbalance price for long deviations at hour t. [€/MWh]

τ Time steps. [h]

θ Incidence angle between the normal to the aperture plane and solar irradiance. [º]

θ_{col} Colector tilt angle. [º]

θ_e Solar elevation. [º]

$\lvert\Delta P\rvert$	Average absolute power error. [MW]
$a_{i,t}$	Noise term of the ID prices prediction time-series model with a $N(0,\sigma_i^2)$ distribution for all t.
A_{SF}	Solar field area. $[m^2]$
APE	Absolute Power Error. [MW]
$APE_{proposed}$	Absolute power error obtained with the proposed optimization method. [MW]
$APE_{standard}$	Absolute power error for the standard optimization method. [MW]
c_i	Model parameter of the ID prices prediction time-series model for each intraday market i.
$c_i^{Startup}$	Cost parameter for unit group i for the start-up of additional capacity. [€/MWh]
CF, FC	Capacity factor.
$CVaR$	Conditional Value at Risk.
$D_{r,t}^{Elec}$	Demand for time step t in region r. [MW]
$desvio_{long}$	Deviation between the standard longitude that set the hour and the real longitude of the location. [º]
DM_{inc}	Incomes obtained in the daily market. [€]
E	Energy produced. [MWh]
$E\left[R;P_i\right]$	Expected revenue because of the wind farm market participation. [€]
e_i	Cost parameter for unit group i for fuel consumption.
E_{str}	Storage capacity for CSP plants. [MWh]
EOT	Equation of time.
F	Fuel.

$f_{CO_2}^{tax}$ Tax on emission of CO_2 from plants. [€/tn]

$f_{F_i}^{price}$ Price of fuel F_i. [€/GJ

f_F^{emis} Emission of CO_2 when burning fuel F. [tn]

f_i Fuel consumption parameter for unit group i when producing power depending on the efficiency of the actual load.

$F_I(z)$ Cumulative Probability Density Function of the incomes.

$F_{s,t,i}$ Fuel use in scenario s for time t for the unit i. [MW]

$g(P_g, \pi_i, \alpha; P_i)$ General expression for the revenue equation, R, of a wind power producer.

i Intraday market session.

I^{elec} Set of power producing unit groups.

I^{fuel} Set of unit groups using fuel.

I^{online} Set of units with minimum restriction of power production.

I^{pump} Set of pumped hydro storage.

I^{ramp} Set of unit groups with ramps restrictions.

$I^{run-of-river}$ Set of units of hydro run of river.

IM_{inc} Incomes obtained in the intraday market. [€]

IT_t Imbalance term (costs/ incomes) due to the imbalance management process. [€]

$j_{i,t}^{biomass}$ Production of biomass power plant i at time step t. [MW]

$j_{i,t}^{CSP}$ Production of thermoelectric power plant i at time step t. [MW]

$j_{i,t}^{inflow}$ Inflow to the hydro reservoirs.

$j_{i,t}^{PV}$ Production of photovoltaic power plant i at time step t. [MW]

$j_{i,t}^{run-of-river}$	Production of run-of-river power plant i at time step t. [MW]
$l_{r,\bar{r}}^{trans,cost}$	Transmission cost per MWh. [€/MW]
$l_{r,\bar{r}}^{trans,max}$	Maximum transmission capacity from region r to $\bar{r}$. [MW]
$latit$	Latitude of location. [º]
$long$	Longitude of location. [º]
$Loss_{pump}$	Factor considering the load loss of electricity storage.
n_α	Number of imbalance price bins.
n_h	Number of hours. [h]
n_P	Number of power bins.
O_i	Operation and maintenance cost parameter for unit group i. [€/MWh]
$p_i^{Maxprod}$	Maximum electricity capacity of unit group i. [MW]
$p_i^{Minprod}$	Minimum electricity capacity of unit group i. [MW]
$P_{d,t}$	Power traded in the daily market. [MW]
$P_{g,t}$	Power actually generated by the wind farm in the period t. [MW]
P_{g_j}	Bin value of generated power, corresponding to the $j-th$ power bin. [MW]
$P_{i,opt}$	Optimal power bid in the IM by the wind farm. [MW]
$P_{i,s,t}$	Realised power output of unit group i in scenario s at time step t. [MW]
$P_{i,s,t}^{online}$	Online capacity of unit group i at time step t. [MW]
$P_{i,s,t}^{Startup}$	Started capacity of unit group i in scenario s at time step t. [MW]
$P_{i,t}$	Estimation of the future produced power in the IM for the wind farm. [MW]

$P_{i,t}^{DM}$	Power of turbine i sold to day-ahead market for time step t. [MW]
P_{inst}	Installed power of each technology. [MW]
$P_i^{Ramp_{rate}}$	Maximum increase/ decrease of power production within an hour. [MW]
$P_{r,\bar{r},s,t}^{trans}$	Transmission from region r to region $\bar{r}$ at time step t. [MW]
$P_{r,t}^{Windshed}$	Wind power shedding in region r at time step t. [MW]
$P_{r,t}^{Wind}$	Actual wind power production capacity in region r at time step t. [MW]
P_r	Rated power of the wind farm. [MW]
Q_{HTF}	Thermal power available in the heat transfer fluid of the CSP plant. [W]
Q_{warm_sf}	Thermal power to warm-up the solar field. [W]
$r, \bar{r}, R$	Region.
R_t	Revenue obtained by a wind farm participating in the electricity market in a period t. [€]
$Ramp_{rate}$	Maximum increase/ decrease ratio of power production within an hour.
s	Scenario.
T	The last time step within a scenario tree.
t	Time steps of the optimization period. [h]
$t_i^{min_{op}}$	Minimum operation time of unit group i. [h]
$t_i^{min_{sd}}$	Minimum shut-down time of unit group i. [h]
t_{str}	Storage hours for the CSP plant. [h]
t_s	Solar time.

$V_{i,s,t}^{hydro}$	Content of hydro storage i at time step t in scenario s. [MWh]
$V_{i,s,t}^{pump}$	Content of electricity storage i at time step t in scenario s. [MWh]
$v_i^{Hydromin}$	Minimum storage content of hydro storage i. [MWh]
$v_i^{Hydromax}$	Maximum storage content of hydro storage i. [MWh]
$v_i^{str,max}$	Maximum storage content of electricity storage i. [MWh]
$V_{ref,t}^{hydro}$	Reference reservoir level at hour t of the reference year. [MWh]
VaR	Value at Risk.
$W_{i,s,t}$	Loading of electricity storage i in scenario s at time step t. [MW]
w_i^{MAX}	Maximum loading capacity of electricity storage i. [MWh]
$Sp_{i,s,T}^{hydro}$	Shadow price for hydro storage content. [€/MWh]
$Sp_{i,s,T}^{online}$	Shadow price for unit i being online at the end of the scenario tree. [€/MWh]
$Sp_{i,s,T}^{pump}$	Shadow price for electricity storage content. [€/MWh]
Sp_{ref}^{hydro}	Reference shadow price for the scenario. [€/MWh]
ARMA	Autoregressive-moving-average model, model for the analysis of seasonal time series.
BP	Buy price, that is, price for short deviations.
CSP	Concentrated Solar Power
DM	Daily market.
DNI	Direct normal irradiance. $[W/m^2]$
FV	Photovoltaic.
IM	Intraday Market.
IP	Imbalance Prices.

JMM	Joint Market Model.
MDP	Marginal daily price.
NBUD	Hourly net balance of up and down energies allocated in the tertiary reserve, secondary reserve markets and the deviation management procedure, if any.
NREAP	National Renewable Energy Action Plan for the Spanish power system in 2020.
OSP	Operation Settlement Period.
PANER	National Renewable Energy Action Plan.
PDF	Probability Density Function.
PV	Photovoltaic.
RBP	Reference Buy Price.
RSP	Reference Sell Price.
SP	Sell price, that is, price for long deviations.
STT	Scenario Tree Tool.
TES	Thermal Energy Storage.
TSO	Transmission system operator.
UT	Update Term, accounts for the participation of wind power producers in IM, including the imbalance term.
WAPD	Weighted average price of management imbalances, tertiary and secondary reserve for down energies.
WAPU	Weighted average price of management imbalances, tertiary and secondary reserve for up energies.

Chapter 1

Introduction

Nowadays power systems have experienced a substantial increase in their renewable installed capacity. This new configuration of the generation mix implies new problems to deal with. Renewable energies strongly depend on the availability of natural resources, such as wind, solar radiation, biomass or waves. In consequence, their power output is highly variable as only some power technologies include some kind of storage, such as concentrating solar power (thermal storage), biomass (partially storable) and pumping units.

Another matter to take into account is the fact that renewable energies are partly predictable. As energy markets have to be programmed in advance a prediction of the future power output is necessary to schedule the generators production in order to supply the demand. The production forecast has usually associated prediction errors, and so power systems schedule has to be calculated in a stochastic manner, in order to take into account the deviations between the forecasted and real productions. Hence future power systems should have a new design of adjustment and reserve markets because of their crucial role to deal with forecast deviations.

Up to now, wind power has been the main renewable energy source for electricity in power systems, although other renewable energies have recently increased their installed capacity. Hereafter renewable energies will increase their production because of environmental considerations, such as the reduction of greenhouse emissions and the scarcity of fossil fuels. In this sense, Directive 98/70/EC promotes the use of renewable energies in European countries. The target of 20% of the overall energy consumption coming from renewable sources is encouraged in the European states.

The integration of variable and partly predictable renewable energies poses new challenges for power systems, that should be approached by a twofold perspective. On one hand, renewable power producers have to deal with the forecasts uncertainty. On the other hand, power systems have to be adapted to new operation modes, and so medium and long term planning studies are necessary to predict the new issues to deal with, and adapt the power system to new operation modes. This work studies both sides of the problem.

The first part of the study approaches the integration of wind power in electricity markets. As wind power production forecast has an implicit uncertainty, the difference between prediction and production will lead to system imbalances. In the Spanish power system, wind farms have to pay for the power deviations and, in consequence, they incur substantial economic expenses. In order to avoid these losses, wind farms may take into account the uncertainty of the prediction by means of using strategic bidding, which aims to increase the revenues of the market participation. This problem is approached in the present work by a stochastic optimization process, which considers the forecasts and associated uncertainties of several variables named wind power, intraday market prices and imbalance prices. The stochastic problem solution will provide the optimal power to be bid in the adjustment markets by the wind farms. A risk-constrained strategy is also included in the analysis, in order to consider the attitude towards risk of wind power producers when bid to market. Another aspect of the problem is the suitability of the current energy policy to penalize imbalances. From the point of view of the regulator, market prices should be adequate signals which encourage the reduction of power system costs, inter alia the imbalances produced because of the difference between the bid and delivered energy. The reschedule of the generation is expensive and so, should be minimized. Therefore, generators should have market signals which reflect the effect of deviations in power system. To analyse this issue, a study of wind farms participation in the Spanish electricity market is included in this work. A new imbalance pricing scheme, that encourages the reduction of deviations, is also proposed.

Another regard included in this work is the assessment of a real case in which the optimal bidding strategy is employed within a real-time tool. The results of the participation of nine wind farms in the Spanish electricity market are presented. In these cases the optimal bidding strategy is employed to select the power bid to market. The presented contributions were part of the European project Anemos.plus.

The second part of the study deals with the overall effect of increasing the installed capacity of renewable energies in the generation mix. Once the participation of one/several wind farms in the power system is evaluated, the next issue to assess is the effect of substantial amounts of renewable energy in the power system. Therefore, the integration of a new portfolio of renewable technologies is studied, and a medium-term planning study of this new configuration is done. The optimal schedule of the generation is then obtained for a future power system with an increased installed capacity of renewable energy sources for electricity (RES-E), by means of solving a unit commitment problem. As input data, the composition of the generation mix and the technical constraints of power plants are considered as well as the RES-E future production series. Due to the increasing importance of the solar energy in the Southern Europe countries, a model for concentrated solar power units is implemented in this work to obtain the Peninsular Spanish production. Therefore, the results of this last model are integrated into the optimisation problem to obtain the generation schedule. Three main aspects are studied in depth in this work, marginal and overall system costs, changes in the generators operation mode and effects on environmental aspects, i.e., greenhouse emissions.

1.1 Objectives

This work aims to:

- Study several strategies of participation of wind farms in the Spanish electricity market.
- Devise possible improvements of the current regulatory frame to prevent inappropriate behaviour of market agents.
- Estimate the effects of these strategies in the Spanish electricity market.
- Analyse the impact of a higher penetration of renewable energies in the generation mix for the Spanish power system. This analysis will include the

economic effects, the operational impact on the generators and the environmental consequences of increasing the renewable generation capacity.

1.2 Tasks

During the development of this study, the following tasks were done to achieve the latter objectives:

- Developing a tool that simulates the behaviour of a wind power generator that tries to maximize its market incomes, from the information available to this generator, that is, the wind power forecast, electricity market prices and uncertainties associated to these variables. This tool is designed considering the Spanish market regulation.
- Analysing the behaviour and characteristics of Spanish electricity market prices in order to study their influence on the strategies adopted by the wind power producers.
- Analysing the current Spanish regulation that set the prices of the generators deviations.
- Devising a new regulatory scheme to set generators imbalance prices and assess its validity for the Spanish system.
- Modelling the future renewable energy sources production under different hypotheses. From this assumptions, several scenarios will be defined and introduced into a unit commitment problem together with technical data of the generation mix.

1.3 Structure

The present document is composed by a main document that outlines the results published in the works included in the appendixes. The main body includes chapters 2 and 3, as well as the principal conclusions and contributions of these works in chapter 4. Later, the appendixes contain the published papers and developed studies.

Chapter 2 presents an outline of the results published by Bueno et al. [1], Moreno et al. [2], Bueno-Lorenzo et al. [3], Moreno et al. [4] that analyse the participation of wind power producers in electricity markets. Chapter 3 includes an overview of the planning study of the Spanish power system in 2020, published by Bueno Lorenzo [5]. Then the main conclusions and contributions of these works are presented in chapter 4.

Finally the appendixes of this thesis gather the published works corresponding to:

- **Appendix A:** Bueno, M., Moreno M.A., Usaola J., Nogales F.J. "Strategic Wind Energy Bidding in Adjustment Markets". Proceedings of the UPEC, Cardiff (United Kingdom), 2010.
- **Appendix B:** Moreno M.A., Bueno, M., Usaola J. "Evaluating risk-constrained bidding strategies in adjustment spot markets for wind power producers". International Journal of Electrical Power & Energy Systems 43 (1), 703-711 (2012).
- **Appendix C:** Bueno, M., Moreno M.A., Usaola J. "Analysis of the imbalance price scheme in the Spanish electricity market: a wind power test case". Energy Policy 62, 1010-1019 (2013).
- **Appendix D:** Moreno M.A., Usaola J., Bueno, M. "Assessing the economic benefit of a bidding decision support tool for wind power producers". IET Renewable Power Generation 7 (6), 707-716 (2013).
- **Appendix E:** Bueno, M. "Efectos de una alta penetración de energías renovables en el sistema eléctrico". Electronic file. [Working paper] (2014). `http://e-archivo.uc3m.es/handle/10016/18440`.

Chapter 2

Strategic bidding of wind power producers in the Spanish electricity market

2.1 Introduction

Intermittent energies should participate in electricity markets. This interaction is twofold; on the one hand, renewable energy sources for electricity (RES-E) assume risks that originate from market participation and, consequently, should pay the costs of the deviations produced in the power system. On the other hand, regulations should enhance RES-E participation, as they possess positive environmental externalities.

Regarding the first issue, in the Spanish electricity market case, wind power producers participate in a similar manner as conventional plants. For this, wind farms should forecast their expected production to bid it to the market during the settlement period. Generally, their production is estimated using short-term wind power prediction tools, which usually provide the forecasted power level and the associated uncertainty. The accuracy of these tools has been widely studied in the literature, including in studies by González et al. [6], Martí et al. [7], Pinson et al. [8]. Today, advances in this field provide rather accurate predictions. However, the deviations between forecasted and committed power produce imbalances, which should be paid by the wind power producers. The effect of these payments is shown in studies by Fabbri et al. [9], Holttinen [10], Bathurst et al. [11]. Therefore, some scientific works have focused on considering the uncertainty of the predictions to reduce the imbalance costs. Given that an estimation of the uncertainty should be provided, several approaches to determine this value can be considered, including those described by Pinson et al. [12], Monteiro et al. [13], Nielsen et al. [14], Pinson et al. [8], Morales et al. [15]. Once the uncertainty has been estimated, several techniques can be used to reduce the effects of deviations from initial schedules. Optimisation strategies can be widely employed to reduce economic losses and, consequently, improve the revenues. Accordingly, these strategies are based on updating the bid made to the daily market in the intraday market, when predictions with shorter horizons are available; the accuracy of the predictions thus rises. These methods can be found in studies by Fabbri et al. [9], Holttinen [10], Angarita-Márquez et al. [16], Usaola & Angarita [17], Usaola & Moreno [18], Bourry & Kariniotakis [19].

However, market participation risks do not only depend on power deviations, as electricity market prices are highly variable and difficult to forecast. Therefore, an estimation of these prices is a relevant problem. Due to the unavoidable difference between the produced and committed power, the imbalance costs borne by wind power producers are especially important, and the imbalance prices should thus be considered. While most studies are not based on actual balancing energy prices and only consider estimations (Holttinen [10], Fabbri et al. [9], Matevosyan & Soder [20], Angarita-Márquez et al. [16]), realistic assumptions can be found in certain studies, such as those presented in this work in appendixes A and B.

In addition to the optimisation strategy, a risk management restriction can be considered in an effort to reduce the hazard of having extremely high imbalance losses or to reduce the deviations produced in the power system. These risk-constrained methods consider the variability of imbalance prices and/or production and address them to reduce the risk of incurring excessive costs. These methods can be found in previous studies by Dicorato et al. [21], Botterud et al. [22], Bourry et al. [23], Dent et al. [24].

In the literature, some works analyse the market design. Most researchers focus on support schemes, such as Rivier-Abbad [25], Klessmann et al. [26], Hiroux & Saguan [27], but the studies also consider other integration issues, including technical and economic aspects. Other articles analyse the design and structure of the balancing prices scheme, such as those by Barth et al. [28], Vandezande et al. [29], Weber [30]. Thus, in these works, a trade-off between the effect of market signals on the behaviour of wind generators and efficient support schemes is suggested, and some policy recommendations are included. Although these works analyse the present regulation, none of them are based on particular test cases.

2.1.1 Objectives and tasks

The aim of this chapter is two-fold; on the one hand, the participation of wind power producers in electricity markets is assessed. On the other hand, the efficiency of the imbalance prices scheme is evaluated.

In order to achieve these goals, the following tasks have been performed. First, an optimisation tool is designed for the participation of wind energy in adjustment markets in order to increase the wind power producer revenues, through a stochastic optimisation process, which considers the uncertainty of the random variables involved, namely short-term wind power prediction, intraday price prediction and imbalance price prediction. Second, the study includes an assessment of the economic benefits of a decision support tool based on a risk-neutral strategy in nine real wind farms. Besides, the tool includes a risk management module. Finally, given the assumption that the regulation of imbalance market prices should foster the reduction of power system balancing costs and, thus, promote the decrease of unexpected deviations, a new imbalance price scheme is proposed.

2.2 Spanish electricity market

The electricity market is composed of a set of markets in which generators participate to sell their hourly power production and other services. Spanish electricity markets are mostly marginal price systems, where the price is set by the equilibrium point between supply and demand. The Spanish electricity market is organised around a daily market (DM). Additionally, adjustment markets take place six times a day to correct forecasted deviations from the initial schedule. Generators bid in the DM their future power output. Afterwards, they may update their productions in the adjustment or intraday markets (IM). Finally, the transmission system operator (TSO) addresses real-time deviations through ancillary services and, if necessary, opens an imbalance management process[1]. These markets processes are explained in the following sections.

For our work, both the imbalance correction process and ancillary services markets are relevant. These latter markets include the secondary and tertiary reserve and the imbalance management process.

2.2.1 Daily and intraday markets

In the DM, bids must be made between 14 and 38 hours before the operation settlement period (OSP). In the Spanish case, the gate closure time is 12 a.m[2]. This market possesses the largest liquidity, as most energy is negotiated in it[3].

The intraday markets may be continuous or composed of several sessions, as in the Spanish case, where 6 intraday market sessions are held. The IMs are also marginal price systems. The Spanish IM sessions occur 4 to 7 hours before the OSP.

In these IMs, producers may sell and purchase energy to compensate for the deviations between the scheduled power production in the DM and the available forecasts at the IM session time.

2.2.2 Imbalance markets

During the interval between the last gate closure of an intraday market session and opening of the next one, deviations between scheduled and measured energy are addressed through ancillary services based on market procedures, such as secondary reserve, tertiary reserve and imbalances management process. This mechanism is regulated by operating procedure 3.3 of the Spanish system operator (BOE [31]).

Once these markets take place, the imbalance prices are set. These prices are paid by generators when their production deviates from the energy committed in the markets.

[1] In the Spanish market this is called *"Mercado de gestión de desvíos."*

[2] Before October 2013 the gate closure time was 10 a.m., and this is the time considered in this work.

[3] Around two thirds of the whole energy is traded in DM.

In the Spanish electricity market a dual imbalance price (IP) scheme is employed that sets different prices for under and over deviations. To determine the price for over deviations, Sell Price (SP), and for under deviations, Buy Price (BP), the TSO calculates the hourly net balance of up and down energies (NBUD) allocated in the tertiary reserve, secondary reserve markets and the deviation management procedure, if any. This balance determines how the prices will be set depending on whether the volumes of imbalances are in the same direction as the overall market. TSO also calculates the weighted average price of the overall down/up energies (WAPD/WAPU), computing the price of management imbalances, tertiary and secondary reserve for down/up energies. If this value (WAPD/WAPU) does not exist, i.e., NBUD is negative for the BP case or positive for the SP case, the imbalance price worth is set to the marginal DM price. This mechanism is explained in depth in section C.6.1.

2.3 Wind power in electricity markets

Generally, wind power producers bid the last power predictions in the daily market and update the committed energy in the intraday markets, when shorter forecast horizons are available and, thus, predictions are more accurate. As there is an unavoidable deviation between the power committed and finally produced, wind power producers frequently incur imbalances. These deviations should be settled at imbalance prices, as these imbalances suppose a burden to wind power producers and have negative effects, thus reducing the incomes obtained during the market participation.

As the IMs have less liquidity than the DMs, some problems may arise with the participation of significant wind power in the IM (very likely buying or selling energy simultaneously). The effect of increased wind power on the IM must still be evaluated and is not considered in this work.

Currently, recent changes in Spanish regulation establish that wind power producers receive a tariff for the energy delivered to the Spanish power system. However, they also settle their deviations from the committed energy at imbalance prices. In these studies a market participation is supposed, which follows the rules of the former regulation. This recent change is temporary, and so, it is possible that wind power producers return to the market participation in the next future.

2.3.1 Revenues of a market participant

The general mathematical expression of the revenue R_t obtained by a wind farm participating in the electricity market in a period t may be generalised as

$$R_t = DM_{inc,t} + IM_{inc,t} + IT_t = P_{d,t}\pi_{d,t} + \pi_{i,t}(P_{i,t} - P_{d,t}) + IT_t \tag{2.1}$$

where DM_{inc} and IM_{inc} are the incomes obtained in the daily and intraday markets, respectively, and IT corresponds to the imbalance term (costs/revenues). Then, the right-side formula expresses the revenues as a function of market prices and powers for a period t, where $P_{d,t}$ and $P_{i,t}$ are the estimations of the future produced power at the gate closure time of the DM and IM, respectively. The forecast of power production is updated at the intraday market time, and the power traded in IM is thus $P_{i,t} - P_{d,t}$, as the power previously committed in DM is $P_{d,t}$ for a given hour t. Furthermore, $\pi_{d,t}$ and $\pi_{i,t}$ are the marginal prices of energy in the DM and IM, and IT_t is the imbalance term for that period t, whose expression is

$$IT_t = \begin{cases} \pi_t^{sell}(P_{g,t} - P_{i,t}) & P_{g,t} > P_{i,t} \\ \pi_t^{buy}(P_{g,t} - P_{i,t}) & P_{g,t} < P_{i,t} \end{cases} \tag{2.2}$$

with $P_{g,t}$ being the power actually generated by the wind farm in the period t and π_t^{sell} and π_t^{buy} being the imbalance prices for overproduction (positive imbalance) and underproduction (negative imbalance), respectively.

Typically, $\pi_t^{sell} \leq \pi_{d,t} \leq \pi_t^{buy}$, and they may be written as

$$\begin{aligned} \pi_t^{sell} &= \alpha_t^{sell}\pi_{d,t} \\ \pi_t^{buy} &= \alpha_t^{buy}\pi_{d,t} \end{aligned} \tag{2.3}$$

with $\alpha_t^{sell} \leq 1$ and $\alpha_t^{buy} \geq 1$.

In the next sections, the variables involved in the problem will be described.

2.3.2 Short-term wind power prediction uncertainty

Forecasting tools can provide deterministic predictions, also called *point predictions*, as well as the uncertainty associated with the prediction. This additional information can be considered when power producers bid to market. In this work the probability density function (PDF) of the wind forecasts is employed to determine the power to bid in market, therefore the uncertainty of the wind power is considered in the problem. Further information about wind forecasts can be found in appendix B.4.

2.4 Optimal bidding strategy

When a wind power producer participates in electricity markets, it is possible to follow an optimised strategy to increase the revenues obtained. These strategies are commonly based on electricity price forecasts, assessing the incomes of participating in several markets under probabilistic assumptions. In this section, the bidding strategy used by wind power producers is mathematically formulated. The subscript t was eliminated from eq. (2.1) because of simplicity in the following expressions. First, the general formulation for the revenue equation for one hour, R, of a wind power producer, which participates in the electricity market, can be expressed as

$$R = g(P_g, \pi_i, \alpha; P_i) \tag{2.4}$$

where α represents imbalance prices ratios, defined by eqs. (2.3). Because g is given by eq. (2.1) and (2.2), and P_g, π_i and α are considered independent random variables, following the same assumptions made in appendix A, the optimisation problem can be posed as

$$\begin{gathered} P_{i,opt} = \arg\ max_{P_i} E\left[R; P_i\right] \\ 0 \leq P_i \leq P_r \end{gathered} \tag{2.5}$$

where $E\left[R; P_i\right]$ is the expected revenue, with $P_{i,opt}$ being the optimal position to be taken in the IM, which accounts for the bid made in the daily market, and P_r is the rated power of the wind farm. The prediction tool described in A.5 is employed to provide the future prices of the intraday market. A deterministic estimate of IM prices is employed in the optimal bidding strategy. This tool can provide the uncertainties of the intraday market prices; however, these values are not included in the optimisation process because of the high computational cost and the limited improvements of its use. Due to the high symmetry of the PDF of the forecasted intraday market prices, the incorporation of these parameters affects negligibly the results of the optimisation process.

Consequently, the objective function of the optimisation problem can be simplified as

$$\overline{R} = E\left[R; P_i\right] = \iint_{-\infty}^{\infty} g(P_g, \alpha; P_i) f(P_g, \alpha)\, dP_g\, d\alpha \tag{2.6}$$

being $f(P_g, \alpha)$ the probability density functions of the random variable R.

This problem may be discretised and solved easily using simple enumeration, and it must be solved for every hour t. Then, the expected revenue for a given power bid in the IM can be expressed as a discrete equation, such as

$$\overline{R} = \sum_{j=1}^{n_P} \sum_{k=1}^{n_\alpha} (g_{j,k}(P_{g_j}, \alpha_k; P_i) f_{j,k}(P_{g_j}, \alpha_k)) \tag{2.7}$$

where

- n_P: number of power bins, that is, the intervals of power considered in the optimization.
- n_α: number of imbalance price bins.
- P_{g_j}: bin value of generated power, corresponding to the $j-th$ power bin. The bin value is taken from the average value of the interval considered in any bin.
- α_k: bin value of imbalance price, corresponding to the $k-th$ alpha bin.

To determine the value of the power bid in the IM, the range of power is divided into intervals, that is, bins, and the average worth of any interval is assigned to P_i. Analogous methods are applied to obtain bin values of generated power and imbalance prices. In the latter, the number of bins is different for each hour of the day, as the PDF is dynamically obtained as a function of historical data.

2.4.1 Uncertainty of market prices

The participation of wind energy producers in electricity markets may imply a prediction of future market prices to enhance the revenues obtained by wind power producers, and so, to improve market integration. It is important to correctly estimate the future market prices to adopt a sensitive behaviour to market signals, thus reducing the probability of incurring expenses.

Moreover, market prices forecasting is a challenge for wind power integration because the characteristics of electricity markets result in the intricate behaviour of market prices.

Intraday market price forecasting tool

Disposed with an accurate forecast of intraday market prices is necessary to improve the market bidding strategies for both producers and consumers. A correct estimate of these prices may be used to reduce imbalance costs.

In this work, the IM price prediction tool uses a time series model, where the structure of the Spanish electricity market is assumed. The model of the prediction tool is explained in depth in appendix A.

Analysis of the imbalance prices uncertainty

In the Spanish electricity market, the imbalance prices are highly variable and difficult to forecast. Due to the unavoidable imbalance between scheduled and generated energy, these imbalance prices are very important for a wind power producer. In fact, in the Spanish power system, wind generators are the source of much of the entire system imbalance, as indicated by the Spanish TSO, Red Eléctrica de España [32].

Imbalance prices also have high volatility because the number of participants and the amount of energy exchanged are relatively low and because of the random nature of the overall imbalances.

In this work, the heuristic approach described in appendix A is followed when imbalances prices are estimated. For this, historical imbalance prices were collected, employing prices of the previous two months to the hour considered to obtain an approximation of their Probability Density Functions, that will be used to construct a separate model for every hour of the day which estimates the future prices. This performance is valid for both the sell and buy prices. Instead of the prices themselves, actual daily market prices are known when the bid is calculated, and so the parameters α_t^{sell} and α_t^{buy}, described in eq. (2.3), were used to employ the DM prices to estimate the imbalance costs/revenues. Subsequently, these estimates are integrated in the optimisation bidding strategy, which is described below.

2.4.2 Risk assessment strategies

Due to the electricity market prices uncertainty, complementing the bidding strategy with a risk management approach may be pursued.

Then, if some risk parameters are selected, the minimum expected incomes will be foreseeable, and it will thus be possible to assess the risk before the bid to market.

Risk constraints aim to avoid the most risky strategies, including the uncertainty of the random variables. This principle means that a suitable measure of this risk should be used to improve the economic results and to produce lower errors in the power system. For this purpose, a risk-constrained parameter may be included in the optimal strategy. The most frequently used parameters to limit risk behaviour are VaR (Value at Risk) and CVaR (Conditional Value at Risk), that are explained in depth in C.5.1.

In this work, the parameter CVaR is selected as a measure of the risk. CVaR is strongly recommended in the literature because of its mathematical behaviour, better convergence properties, and its increased sensitivity to extremely risky situations, as it provides a measure of the average tail losses of the probabilistic distribution and not only a lower limit.

Consequently, the optimisation problem can be formulated as follows:

$$\begin{array}{rll} P_{i,opt} = & \arg\, max_{P_i} & E[g(P_g, P_i, \alpha^b, \alpha^s; P_i)] \\ & s.t. & CVaR_{\beta(I)} \geq \omega \end{array} \tag{2.8}$$

where,

- $g(P_g, P_i, \alpha^b, \alpha^s; P_i)$ is the revenues function of the wind power producer.
- $CVaR$ is the parameter employed in the risk management strategy. It measures minimum revenues.
- β is the confidence level for CVaR.
- ω is the threshold of CVaR, i.e., the minimum required value for the incomes.

2.5 Study cases

Several test cases have been prepared following the rules of the Spanish electricity markets. The assumptions followed in the study are:

- The market is a pool with marginal prices. This is valid both for the daily market and for the adjustment (intraday) markets.
- Wind producers make their bids for a given amount of power at zero price and bids are always accepted.
- Prices in the intraday market do not depend on the amount of wind power bid (the IM is sufficiently liquid).
- Hourly power committed at the day-ahead market is updated only once in the adjustment market.

The data of wind farm used in the simulation studies come from the actual production of a wind farm during a period of nearly a year, except in case C, in which the production of nine wind farms is taken.

Historical data of intraday and imbalance prices of the Spanish market have been used to forecast the imbalance prices and to estimate the imbalance costs using the model developed, respectively (taking a two month moving window). Prices of the Spanish electricity market may be obtained from OMEL [33] and E-sios [34].

2.5.1 Case A. Trading decision support tool

In this test case, the performance of a real time optimisation tool for the participation in electricity markets of wind farms is evaluated. For this, wind power predictions and their uncertainties (in form of probabilistic intervals, that is, quantiles) are supplied by a prediction tool [4]. The results for nine wind farms with a total installed power of 317 MW are presented. Non risk-constrained strategies have been employed in this case. Historic and actual market prices are obtained in the same manner than in the other cases. The study is done for the whole year 2010. Further explanations can be found in appendix D.

[4] This tool was developed by ARMINES/Paris Tech (École Nationale Supérieure des Mines de Paris) in the framework of the Anemos.plus project.

2.5.2 Case B. Evaluation of risk constrained strategies

In this test case a wind power producer participates in the Spanish electricity markets during a period of 10 months in 2007, from March to December.

The data of wind power come from the actual production and forecasts of a 21 MW wind farm, taken from the ANEMOS project. Historic production and forecasts with time horizons up to 38 hours were used to compute the PDF of forecasts, as an approach to a probabilistic forecasting model for wind power production.

The revenues increase by using the optimisation tool is assessed. A risk management strategy is also included. This work is extended in appendix B.

2.5.3 Case C. Analysis of the imbalance price scheme

In this test case a new imbalance price scheme is proposed and evaluated. For this, the production and forecasts of the wind farm employed in the case A are used (a 21 MW wind farm). The study also includes a risk management strategy. The evaluation is done during a period of 10 months in 2007, from March to December.

The proposed imbalance price scheme indexes imbalance prices to both DM and IM prices, instead of exclusively to DM price as in the current pricing scheme, in order to decrease the imbalances, independently of the cost of deviations in the power system. Then this regulation includes, as a new constraint, that the BP (Buy Price)/SP (Sell Price) must be higher/lower or equal than both the intraday prices (π_i^n) and the marginal daily prices (π_d). Therefore, the new Reference Buy Price (RBP) and Reference Sell Price (RSP) could be defined as

$$RBP = max(\pi_d, \pi_i^1, ..., \pi_i^6)$$

$$RSP = min(\pi_d, \pi_i^1, ..., \pi_i^6)$$

The results of this study are explained in depth in appendix C, where this imbalance price proposal is exhaustively presented.

2.6 Results

In this section only a selection of the results are given. The complete results are presented in the respective appendix. To analyse the results, some variables are compared.

- Revenues, R (€): Incomes obtained by a wind power producer resulting from its market participation.

- Power Error (MW): difference between power bid at intraday market gate closure ($P_{i,t}$) and power delivered to the power system ($P_{g,t}$).

$$\Delta P_t = P_{i,t} - P_{g,t} \tag{2.9}$$

- Absolute Power Error (APE) (MW): power error absolute value.

$$|\Delta P|_t = |P_{i,t} - P_{g,t}| \tag{2.10}$$

The average hourly value is provided in terms of both power error and absolute power error.

To assess the performance of the tool, the results are compared with those obtained following the usual strategy adopted by wind power producers when bidding to the Spanish electricity market, that is, to bid the point prediction. This assumption is called reference case. Another additional strategy is also included in case B comparisons, that is, that the wind farm only participates in the daily market bidding the last point prediction available. This strategy is called DM (daily market).

2.6.1 Case A. Trading decision support tool

The simulation results of the reference (point prediction) strategy and the proposed strategy (non risk-constrained optimisation) for nine real wind farms by means of using the trading tool are presented in Table 2.1. Benefits of the proposed strategy vs. the reference one are also shown, both in € and in %. It may be seen that better results are obtained for all the wind farms selected in the demonstration case. The total benefit obtained by using the strategic bidding tool is 321,200 €, which leads to an increase of 1.3% over the reference method revenue for these wind farms.

In this case, the tool does not minimize the absolute power error, but on the contrary, it increases in all the cases, as it can be observed in Figure 2.1. This behaviour confirms the idea that the most accurate prediction of wind power production does not lead to the highest revenues. From Figure 2.1, the wind farm

Wind Farm	Installed capacity (MW)	Proposed method revenue (M€)	Standard method revenue (M€)	Benefit	
				(€)	(%)
A	33	3.57	3.55	20,300	0.6%
B	24	1.54	1.51	33,600	2.2%
C	21	1.68	1.68	2,200	0.1%
D	36	2.65	2.62	30,800	1.2%
E	33	2.34	2.28	60,800	2.7%
F	21	1.65	1.62	28,000	1.7%
G	50	3.38	3.29	92,800	2.8%
H	49	4.56	4.53	30,300	0.7%
I	50	4.16	4.14	22,400	0.5%
Total	317	25.54	25.22	321,200	1.3%

Table 2.1: Revenues obtained with proposed and standard methods.

G is the most difficult to predict, but it is the one with larger increase of profits (from Table 2.1).

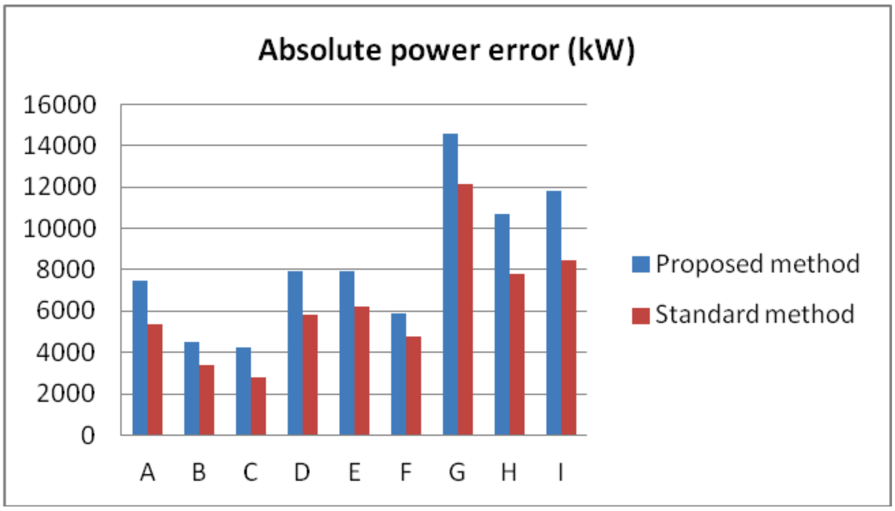


Figure 2.1: Absolute power error for each wind farm

2.6.2 Case B. Risk constrained strategies

Optimal strategy

The results inferred from the optimal strategy without risk management compared with those from the point forecast strategy are summarized in Table 2.2. R represents the total incomes obtained by any strategy, and R_{IM} and R_I indicates the obtained incomes in the intraday and daily markets respectively. The table results show that the optimal strategy increases in a 0.75% the total revenue for the wind power producer over a period of ten months, giving a profit of 10,400 € (1,040 € per month in average).

As the total revenue increases, the average absolute power error increases in a higher percentage (72%), showing that the most profitable strategy for the wind power producer is not the one that minimizes the imbalances between the contracted and actual energy production.

	Optimal	Point forecast	Difference (%)
R (M€)	1.4028	1.3924	+ 0.75
R_{IM} (€)	237,585	-30,384	+ 882
R_I (€)	-358,516	-100,871	- 255
$\lvert\Delta P\rvert$ (MW)	3.0677	1.7874	+ 72

Table 2.2: Total revenues and power error for the optimal strategy vs. point forecast strategy.

Optimal risk-constrained strategy

The risk constraints were applied for several CVaR thresholds, from -1000 € to 1000 € in steps of 100 €. Controlling the threshold is a way of controlling the risk aversion, as it increases with higher values of the threshold.

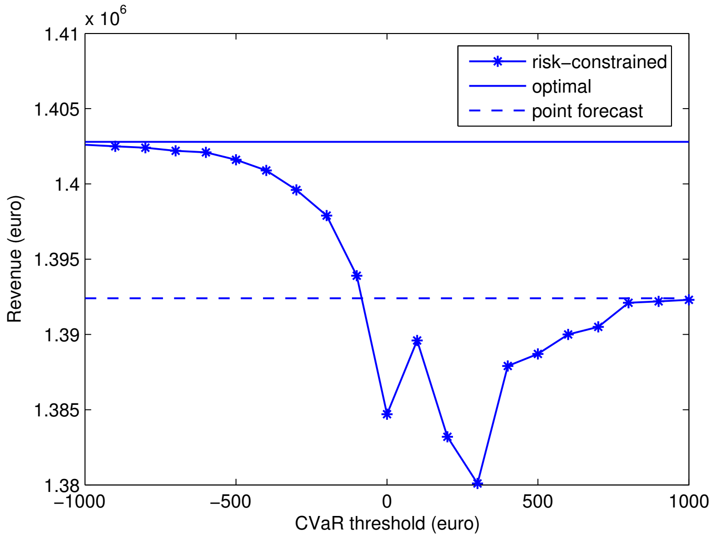
Results are plotted in figure 2.2. The revenues obtained with the different thresholds in the risk-constrained strategy are depicted in Figure 2.2(1). Also the total revenue obtained with both non-risk-constrained strategies (optimal and point forecast) are included in the same figure for an easier comparison of results. It can be observed, on the one hand, that the more severe the restriction (i.e., greater CVaR threshold), the more similar is the result to that obtained with point forecasts. On the other hand, if risk aversion is low (lower CVaR threshold), revenues tend to the value obtained with the optimal strategy.

Regarding the power errors, the average absolute power errors obtained with the different strategies are depicted in Figure 2.2(2). When the revenue is limited by the values obtained with the non-risk-constrained strategies (this happens for negative CVaR thresholds, as seen in Figure 2.2(1)), the average power error is always greater than the power error of the optimal strategy, and therefore, the risk-constrained strategy does not benefit the power system either.

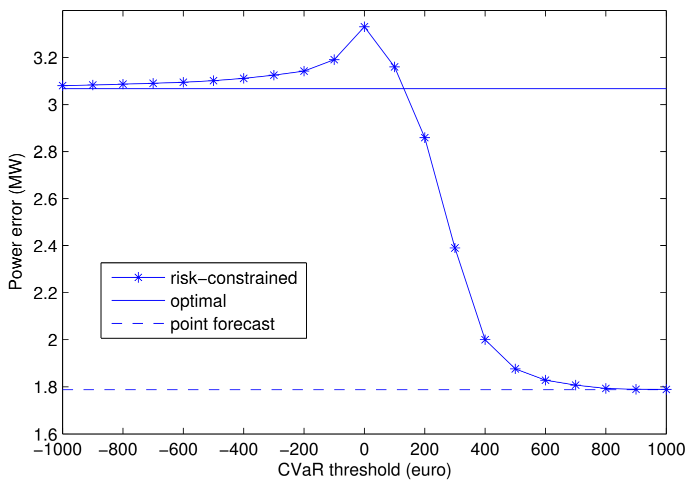
2.6.3 Case C. Analysis of the imbalance price scheme.

Results from the optimal strategy, with and without risk constraints, are analysed in figure 2.3 which shows the relationship of aggregated deviations and incomes.

In this figure, the incomes vs. absolute power error average values are represented for both current and proposed imbalance price schemes. The dark symbols



(1) Revenues.



(2) Average absolute power error.

Figure 2.2: Results obtained with the different strategies.

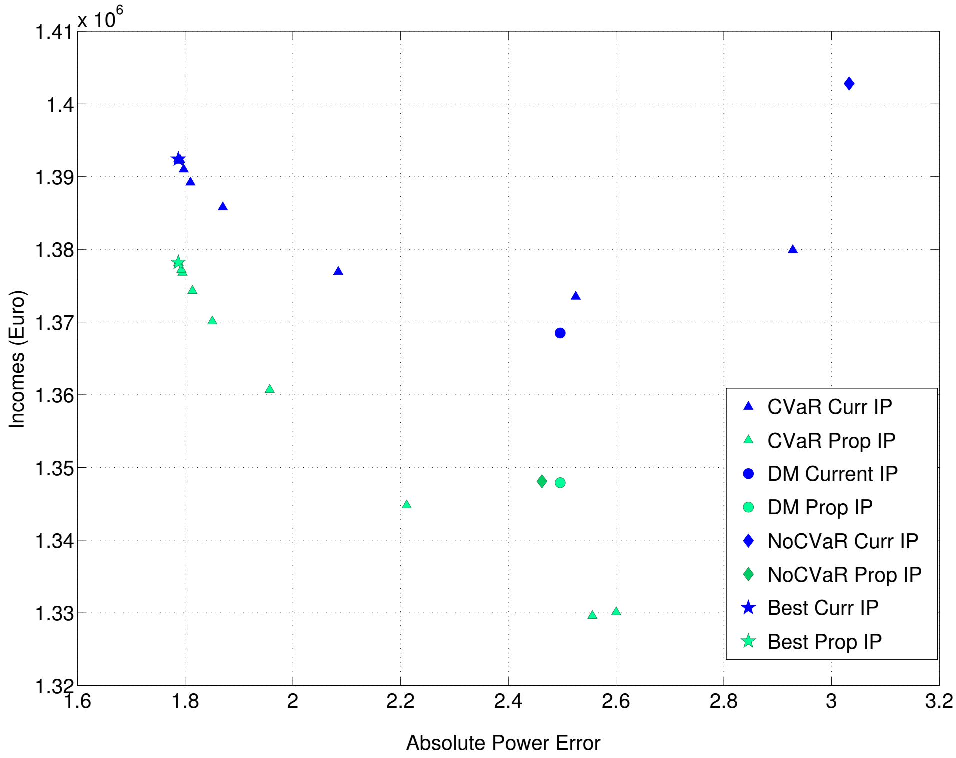


Figure 2.3: Incomes vs. Absolute Power Error

correspond to the current IP scheme, while the light markers represent the proposed regulatory scheme. Moreover, triangles depict CVaR strategies, diamonds represent optimisation strategies without CVaR restrictions, circles correspond to reference DM and stars depict reference ID strategy (called Best).

Based on the results of the current IP scheme (dark symbols), while the incomes are correlated with absolute errors for diverse CVaR values and reference cases, this dependence is not observed in the optimisation without CVaR, where it can be appreciated that higher incomes have been obtained when absolute power errors are higher. Thus, obtaining better revenues could be based more on obtaining better price forecasts than on producing less power errors. In fact, in this regulation, the best economic results are not those that produce less deviations to the power system.

In the proposed regulation (pale markers), there is a linear correlation between absolute errors and revenues in the CVaR optimisation cases. In this regulation, the maximum incomes are those associated with the smallest power deviations (point prediction bid to the IM). In these cases, some atypical values that do not meet the relationship between incomes and power errors can be observed in the DM reference case and No CVaR optimisation strategy.

From the comparison of both regulations, it can be deduced that the proposed regulation fosters a reduction of deviations.

2.7 Conclusions

From the studies developed, the next conclusions can be extracted:

- Due to the uncertainties in wind power forecasting, the imbalances influence strongly wind power revenues, and this implies a decrease in the wind farms economic benefits.

- Integration of intraday price forecasting in strategic bidding improves revenues for wind power producers.

- An adequate estimate of imbalance prices integrated in the bidding strategy leads to an increase in revenues for a wind participant. Two ways of estimation have been tested and their results have been compared with those of the usual strategy based on bidding point predictions.

- High volatility in prices is a characteristic of certain electricity markets with low liquidity. For the imbalance prices, this high volatility together with its random nature, make their estimation very complex, and hence high imbalance prices may cause important losses for wind power producers.

- Strategic bidding in the intraday market can be used to improve even more the revenues of the wind power producer. The optimal strategy described in this work includes deterministic intraday price forecasting as well as probabilistic power forecasting and probabilistic imbalance prices forecasting from historical data. The strategy tends to sell more energy in the intraday market than forecasted, improving the incomes in that market although the imbalances between contracted and actual production increase.

- A study has been made for nine wind farms spread in a wide area of the Spanish territory and in accordance to the Spanish market rules. For the examined cases, the revenues were overall increased in a 1.3% but, in some wind farms, benefits have exceeded 2.5%. The proposed method improves the traditional one in all the wind farms considered, leading to higher revenues for the wind power producer but also to a higher energy imbalance.

- When applying a risk management strategy, lower risk aversion yields higher revenues, being the upper limit the non risk-constrained strategy (optimal). It is also shown that a decrease in the imbalance costs does not imply an increase in the revenues. The risk-constrained strategy seems to benefit neither the wind power producer, nor the electric power system, because the higher losses of the optimal strategy are not avoided and power errors are greater.

- The regulation of the imbalance prices may not be adequate for the Spanish electricity market because a power error drop is not sufficiently encouraged. The incomes obtained by the wind power producers are not completely correlated with their contribution to the overall power deviations. Indeed, in the test case, higher deviations imply higher incomes.

- Alternative imbalance price schemes could enhance the reduction of deviations in the power system. Along these lines, we suggest the application of a new imbalance price scheme, which includes the indexing of imbalance prices to intraday market prices to avoid those cases in which deviations are not adequately penalised.

Chapter 3

Effects of the integration of renewable energies in the Spanish power system

3.1 Introduction

In recent years, there has been a large increase in the presence of the RES-E (renewable energy sources for electricity) in power systems. So far, wind energy has experienced a substantial increase in its installed capacity, so most studies have focused on evaluating wind power effects on the power system.

The increased share of wind energy has changed both electricity markets and power system functioning, including conventional plants operation. From the viewpoint of the grid management, an increase of the congestions has been experienced. Regarding the schedule of the generation, reserves have increased due to the variability and partial predictability of wind power, that often involves an overestimation of their values. Besides, power plants using fuel have changed their operation mode to accommodate wind production. Due to both, variability and prediction errors of wind power, conventional plants have to increase the number of start-ups and the partially load operation mode. These last two features have harmful effects on the life time of such plants and, therefore, the variable costs of these plants will rise. Both, a more severe use of generators ramps and part-load operation of conventional units, lead to a lower efficiency for power plants using fuel.

Regarding market prices, since RES-E plants have a marginal cost equal to zero, prices will diminish in the short-term, given a higher capacity of RES-E, while their volatility will increase. Another economic effect is the cost of increasing reserves and the inclusion of capacity payments.

Holttinen et al. [35, 36] present the comparative results of integration studies of wind energy in several countries, such as Ireland, UK, Germany, Denmark, Finland, United States, Portugal, Holland and Spain.

In addition to evaluating the effects of wind energy in power systems, in countries with abundant solar resource, such as in southern Europe, studying the effects of power systems with high share of RES-E that are not based solely on wind power is necessary, including a high proportion of photovoltaic and solar thermal energy in the generation portfolio. Considering this fact, a model of solar thermal energy has been carried out, that is explained in detail in section E.2.1.

Several approaches may be employed to assess functioning of future power systems with increasing share of RES-E. García Casals et al. [37] quantify and technically evaluate the feasibility of a power system operated exclusively by renewable energy in the Spanish peninsular system. Another approach is the study of the optimal investment path in technologies for long-term planning. The Balmorel model (Balmorel [38]) analyses energy and heating systems, evaluating investment alternatives for the future portfolio to determine the optimal investment path. This model is employed by Karlsson & Meibom [39] where an optimal path is found to achieve a 70% share of transport consumption coming from renewable sources. Münster & Meibom [40] analyse the use of waste to produce electricity in the Nordic countries in 2025. Juul & Meibom [41, 42] study the integration of power and transport systems in 2030 in Nordic countries and Germany.

To analyse the effects of a future generation mix in the power system, a model of unit commitment is employed. As a result, the number of operating units in each hour as well as the power supplied by them is determined.

The complete developed study is presented in appendix E, and in this chapter, a summary with the main issues, results and conclusions is included.

3.1.1 Objectives and tasks

This works aims to:

- Assess operating costs of a generation mix with a higher share of renewable energies.
- Evaluate the influence of a high share of renewable energy on the operation of plants using fuel.
- Appraise the reduction of greenhouse emissions under different scenarios and compliance with the Kyoto protocol.

In order to achieve these objectives the following tasks were developed:

- Modelling the Spanish power system, including the characteristics of thermal plants and their technical restrictions.
- Obtaining the hourly production of solar thermal power plants from their rated power, storage capacity, size of solar field, location and future series of irradiation by modelling their operation.
- Estimating hourly series of production from other renewable power plants in the future peninsular Spanish power system: wind, biomass, photovoltaic, hydroelectric (run of river, reservoirs).
- Generating deterministic scenarios of hydro power production for the generation mix of 2020 in the peninsular Spain, taking into account different meteorological years.
- Outlining different hypotheses for CO_2 emissions to be included in the scenarios.
- Implementing a module to model the thermoelectric production of concentrated solar power units, that will be included in the unit commitment tool.
- Comparing the results of the different scenarios.

3.1.2 Implemented study

The general characteristics of the implemented model are:

- Geographical scope: peninsular Spain.

- Model: deterministic. Prediction errors are not included.

- Future scenarios: different generation mix, forecasted demand and renewable power prediction series.

The installed capacity of renewable energies has been taken from National Renewable Energy Action Plan (NREAP) assumptions. This plan was elaborated according to the European directive 2009/28/EC, which establishes a 20% gross energy consumption coming from renewable sources. A scenario which deviates from this target is also considered, based on the actual installed capacity of renewable technologies and the growth in past years. The demand in this scenario is also re-calculated from actual deviations.

3.2 Unit commitment problem

The general formulation of a unit commitment problem tries to minimise the power system costs. Here, a general formulation is presented that only includes the general terms of the objective function taken into account.

$$\begin{aligned} min\, V_{OBJ} = &\, Fuel\ Costs\ +\ Operation\&Maintenance\ Costs + \\ &\, Startup\ \ Costs\ +\ Emission\ Taxes\ +\ Transmission\ Costs \\ &\, -\ Capacity\ Online\ -\ Reservoir\ Storage\ -\ Electricity\ Storage \end{aligned} \tag{3.1}$$

The detailed formulation of the problem can be found in appendix E. The objective function terms represent the power system expenses. The first term of the objective function calculates the consumption fuel during the optimisation. The second corresponds to the operation and maintenance costs. Then, the costs due to units start-ups are included. After, carbon dioxide emission costs are added. Finally, the cost of the transmissions between regions are summed up.

Taking into account the value associated to the online capacity of running units is also necessary. Similarly, the value of the energy stored in reservoirs is computed, and additionally, the worth of energy stored in pumping facilities.

The restrictions are described as follows:

Restriction 1. Equilibrium between generation and demand in the daily market (DM), eq. (E.2) of appendix E.

Restriction 2. Maximum power delivered by each plant, eq. (E.3).

Restriction 3. Minimum power limit of each generation unit, eq. (E.4).

Restriction 4. Costs due to fuel consumption for each power plant, eq. (E.5).

Restriction 5. Ramp rates, that is, the maximum/minimum power that could be incremented/diminished for each period by any generation unit, eq. (E.6).

Restriction 6. Maximum storage capacity for the pumping units, eq. (E.7).

Restriction 7. Minimum operation time for the plants, eq. (E.8).

Restriction 8. Minimum shut-down time, eq. (E.9).

Restriction 9. Maximum transmission capacity between regions, eq. (E.10).

Restriction 10. Wind spilled energy or wind shedding, eq. (E.11).

Restriction 11. Start-up capacity, eq. (E.12).

Restriction 12. Ramp restrictions as a function of the online capacity, eq. (E.13).

Restriction 13. Maximum and minimum hydro capacity, eq. (E.14) and eq. (E.15), respectively.

Restriction 14. Balance equation for hydro reservoirs, eq. (E.16).

Restriction 15. Maximum hydro production for an optimisation period t, eq. (E.17).

Restriction 16. Dynamic equation for the pumping storage units, eq. (E.18).

Restriction 17. Maximum loading capacity for pumping units, eq. (E.19).

Restriction 18. Maximum capacity of electricity storages, eq. (E.20).

Restriction 19. Minimum operation and shut-down time, eq. (E.21) and eq. (E.22), respectively.

Variables, sets and parameters are explained in tables of appendix E.1.4.

3.3 Wilmar planning tool

Several tools may be employed to implement a unit commitment model. In this work, Wilmar planning tool is selected because of its many features. This tool is programmed in GAMS (General Algebraic Modelling System). Its performance is described by Meibom et al. [43], Barth et al. [44], and further information may be found in this work in appendix E.1.5. In the Wilmar project, a market model was implemented. This model includes daily, intraday and reserves markets. A thermal market is also included. Moreover, a scenario tree tool was implemented, which considers the uncertainties of renewable energies production, demand and reserves forecasts. With regard to its structure, Kiviluoma & Meibom [45] make a description of the information included in any database.

Wilmar has been employed to analyse Nordic countries and Germany in studies by Barth et al. [46], Meibom et al. [47, 48], Brand et al. [49]. In these studies, future prices and generation productions are estimated for Germany and Nordic countries in 2010, considering high penetrations of wind power. System costs for future power systems are also estimated using Wilmar.

The tool was also adapted to assess the integration of renewable energies in an insular power system, Ireland. The results of this analysis were published by Troy et al. [50], Gubina et al. [51], Meibom et al. [52, 53], Tuohy et al. [54, 55].

Eq. (3.1) determines the schedule of the generation for the considered problem. In this case, only one region, the peninsular Spanish power system, is included in the model and so, transmission constraints has not been considered. The objective function also contains slack variables for those cases in which some constraints are violated. Forced and planned outages are neither included in this study.

This optimisation problem is linear. As integer variables are not considered, an auxiliary variable, named online capacity, $P_{i,s,t}^{online}$ is employed to describe the states of the units (connected/disconnected). This additional variable is used as a linear approximation to calculate start-up costs, minimum and maximum power restrictions and shut-down and operation times.

The characteristics of the employed model are detailed as follows:

- Coal, concentrated solar power (CSP), biomass, combined heat and power (CHP), wind power, hydro and pumping units are aggregated into unit groups, which are considered as an unique unit with the equivalent parameters of the aggregation. In the case of the natural gas units, any plant is independently modelled.

- An aggregated basin is modelled. Instead of using a cascade model for the basins, the addition of stored energy, inflows and capacity of all basins in the region are considered.

- A deterministic problem is solved. Therefore, prediction errors of renewable energies production are not included in the model.

Then a linear model has been employed in this work, which optimises the national production according to the structure of the generation mix.

3.4 Renewable energies model

This section describes the implemented models, that are employed to estimate the renewable energy hourly production.

3.4.1 Concentrated solar power

Several models of CSP plants have been implemented, such as studies developed by Montes et al. [56], Wagner & Gilman [57]. The assumptions taken in the latter have been employed as the basis for the model developed here.

In this work a parabolic trough technology has been selected to model the CSP functioning, because of its widespread deployment in the Spanish generation mix. This technology is composed by arrays of parabolic reflectors, which address the light to concentrators allocated along the reflectors focal line. This receiver is filled with a working fluid, which is heated up to 500 ºC. The reflectors track the sun during the day.

This work aims to develop a simplified model of the parabolic trough, which obtains the hourly production in peninsular Spain from solar irradiation and the characteristics of the plants, such as location, installed power, solar field size and storage capacity. Results of the model are integrated in the Wilmar planning tool to schedule the generation of the power system. This model is explained in depth in appendix E.2.1.

The CSP plant consists of the following modules, which have been independently modelled:

1. **Solar field.** The collector is the device of the solar field which reflects the solar irradiation to the receiver. To determine the solar flux in the receiver, and so the thermal energy available, we must consider both constant and variable optical losses of the collectors.

   The total incoming radiation in the solar field, Q_{SF} (W), can be determined as:

   $$Q_{SF} = DNI\ A_{SF}\ cos(\theta) \tag{3.2}$$

   where DNI is the direct normal irradiance (W/m^2) from the sun; A_{SF} is the equivalent aperture area of the collectors (m^2), that is, the total reflective area of the collectors; and θ is the incidence angle, i.e., the angle between the normal to the aperture plane and the normal solar irradiance. The deduction of the value of this angle is widely explained in appendix E.2.1 and in the book by Kalogirou [58].

   Generally, collectors may follow a single axis-tracking. Typically the axis is oriented in N-S horizontal axis, with E-W tracking. The advantage of this configuration is that very small shadowing effects can be encountered when more than one collector is employed.

   Losses in collector have been considered in the model, such as those due to collector defocusing, transient effects and optical efficiencies.

   The necessary energy to heat the solar field has been also calculated following the considerations by Usaola [59].

   Then the thermal power available in the heat transfer fluid, Q_{HTF} (W), may be formulated as:

   $$Q_{HTF} = \left(DNI\ A_{SF}\ cos(\theta)\ \eta_{col}\right) - Q_{warm\_sf} \tag{3.3}$$

   being η_{col} the overall efficiency of the collector, including the optical and other losses, and Q_{warm_sf} (W) the thermal power to heat the solar field.

2. **Power cycle.** In the power cycle module, thermal energy is converted into useful mechanical or electrical energy. This module contains all the necessary equipment for this task. In the case of large-scale utilities, a steam Rankine cycle with electricity generation is employed.

   The efficiency of the energy conversion is variable and depends on the available thermal energy at the input of the turbine. The range of values has been obtained from the data of NREL [60], and the deducted formula is explained in depth in appendix E.2.1.

3. **Thermal storage.** Some CSP plants include a thermal energy storage (TES) system which allows them to storage energy in intervals with high availability of solar resource. Later, they can use this energy to increase the power production in periods when low solar resource is available, such as weather transients; they can also produce energy when there is no solar resource or shift the operating hours to periods of peak demand. Then, the total TES capacity, E_{str} (Wh), can be defined as:

$$E_{str} = \frac{\dot{W}_{des}\, t_{str}}{\eta_{cycle,des}} \tag{3.4}$$

   where $\dot{W}_{des}$ (W) is the generated power at the design point, t_{str} are the number of hours of storage and $\eta_{cycle,des}$ is the efficiency of the storage at the design point.

For the constructed model, the following data have been used:

- DNI is taken from NREL [60] and Satel-Light [61] databases. Later these values are normalised and multiplied by the month average values of past 22 years taken from NASA [62].
- Technical parameters of plants are collected from NREL [60].
- Installed capacity, location and storage capacity of power plants are gathered from Protermosolar [63].

For the model performance, all plants from the same location have been aggregated, and so they have been simulated as one plant with regard to rated power, solar field area and capacity of the storage. We are assuming that the future installed capacity will have the same spatial distribution as the current one, and to obtain the future hourly production of peninsular Spain, the results of the model will be up-scaled considering the future installed capacity.

Results of the model.

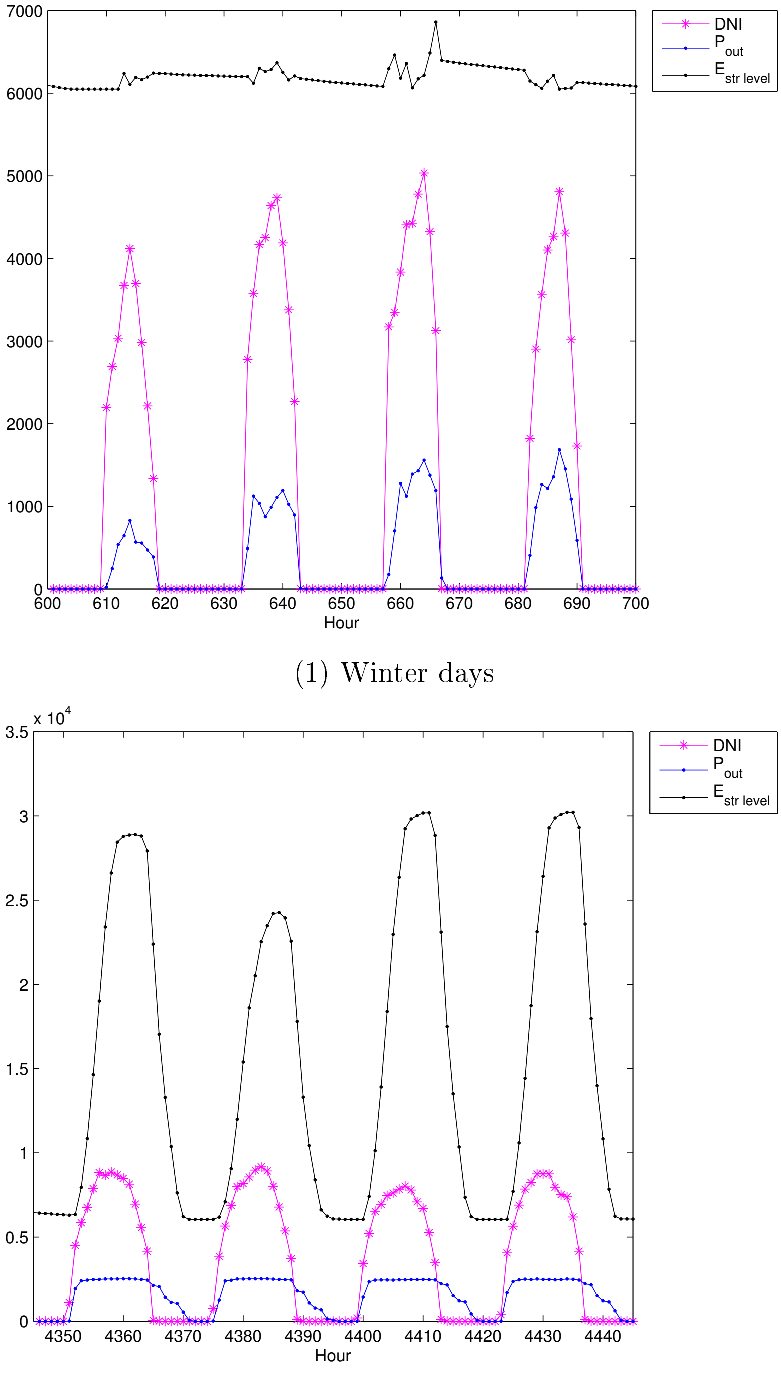
In table 3.1, the hypotheses assumed for the different locations are shown as well as results obtained in their simulations.

Location	Rated power (MW)	TES thermal capacity (MWh)	Storage hours	Annual energy (GWh)
Alicante	50.0	0.0	1478.71	96.75
Badajoz	600.0	3525.0	1950.80	1558.96
Cáceres	350.0	1150.0	1612.16	779.90
Cádiz	100.0	750.0	1640.26	233.53
Ciudad Real	470.4	3250.0	2095.19	1295.78
Córdoba	300.0	675.0	1794.87	702.95
Granada	150.0	1125.0	2431.72	457.53
Lleida	22.5	0.0	1499.01	45.79
Murcia	31.4	15.7	1462.02	66.03
Sevilla	450.0	1280.0	2099.54	1187.79
Total	2524.3	11770.7	2545	6426.29

Table 3.1: Annual results and hypotheses of the CSP model

Aggregated results for the peninsular Spanish facilities are depicted in figure 3.1. Results for four typical winter (figure 3.1(1)) and summer days (figure 3.1(2)) are represented. The DNI is plotted in magenta, the energy stored in the TES is drawn in black and the power output is depicted in blue. During the winter days there is not production from the storage, while in summer there is production out of daylight hours, that comes from the TES system.

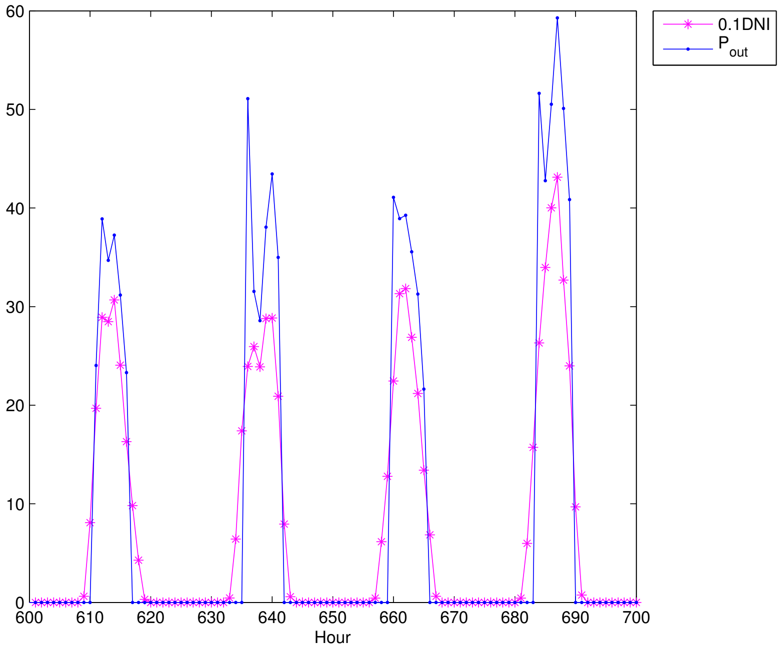
Individual results for a CSP plant located in Cádiz are shown in figure 3.2. By comparing peninsular and regional results the effect of the aggregation can be appreciated in the steps of the power delivered out of daylight hours, that is, when



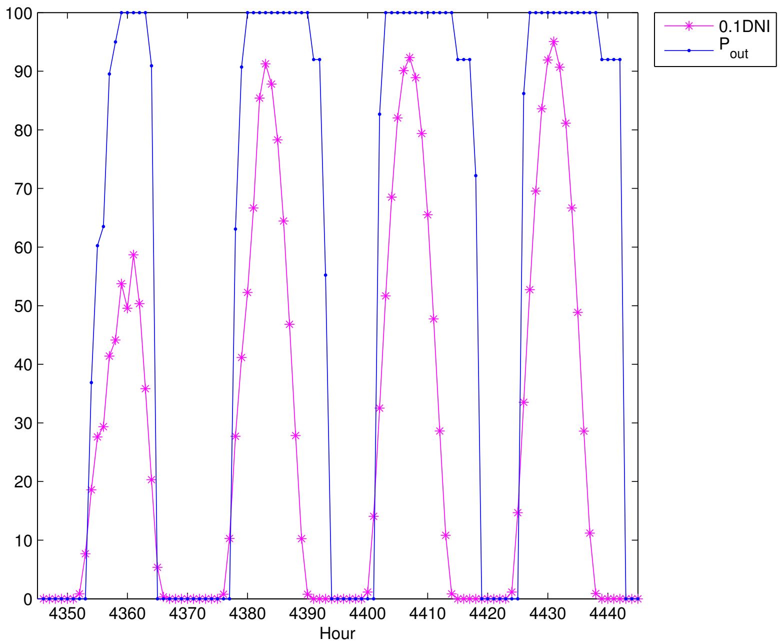
(1) Winter days

(2) Summer days

Figure 3.1: Output power (MW), irradiance (W/m^2) and thermal storage level (MWh) for the aggregated Spanish CSP plants in typical days.



(1) Winter days



(2) Summer days

Figure 3.2: Output power (MW), irradiance (W/m^2) and thermal storage level (MWh) in CSP plants in Cádiz in typical days.

the production comes exclusively from the TES. Further results are presented in appendix E.2.1.

3.4.2 Hydro power

Modelling the hydro production is particularly complex due to the stochastic nature of the rainfall, the hourly variation of their inflows and the geographic dispersion of precipitations. Nevertheless, the possibility of storing the water makes the available hydro power vary smoothly. In the Spanish case, the use of hydro power is also restricted by the river basins regulation.

There are two kinds of hydro power, unregulated hydro inflow and hydro inflow to reservoirs, that are separately modelled here.

Wilmar model uses the inflows and reservoir levels (historical and optimization results) as input data to compute the hourly production. Due to the irregular rainfall along the years, the annual periods are classified into dry, medium or humid. Based on these ranks, the hourly reservoir levels are used as a reference to determine the available energy for hydro power in each scenario, depending on the hypothesis made for the yearly precipitations. All the reservoirs in the peninsular Spain have been aggregated in the model.

In a unit commitment model, the use of hydro power must be limited because of the scarcity of the resource. To avoid excessive consumption of this energy a schedule of the production is necessary, otherwise the model would not take into account the restrictions of use. For this purpose, a shadow price for hydro power is set. First of all, a reference shadow price for each scenario is defined from the marginal cost of the plants using fuel that are replaced by hydro plants. Later, the hourly shadow price will be determined from the reference price and the relative reservoir level, that is, the difference between the level of reservoir of the reference year and the level calculated as a result of the simulation. So, the shadow price increases with respect to the reference shadow price when the actual reservoir level is lower than the historical one, and decreases otherwise.

3.4.3 Other models

The remaining renewable energies have been modelled from historical series of production. Later the historical production is up-scaled by the yearly production forecasted by NREAP. Demand is calculated in the same way. The primary and secondary reserves values are taken as a fix value that is deduced from historical data. These considerations are extended in sections E.2.3, E.2.4 and E.2.5.

3.5 Results

The Wilmar planning tool supplies the generation units production schedule of the Spanish power system in 2020. The optimisation problem was solved using GAMS optimisation tool, employing the CPLEX solver. The formulation of the problem was adapted to the Spanish power system. This model is a first approach to the analysis of the power system with high share of renewable energies, in which a deterministic problem was solved.

3.5.1 Data

The data used in this study was obtained from the following sources:

- Renewable energy production: the yearly production was obtained from the Spanish NREAP forecasts (Ministry of Industry, Energy and Tourism, MINETUR [64]), and the hourly series are based on historical data from E-sios [34], except in the case of the hydro power series that were supplied by the transmission system operator, REE.

- Generation plants portfolio data. The actual installed capacity of the generation plants using fuel is supposed in this study, and individual data was taken from Platts database, Mc Graw Hill Financial [65].

- Coal and natural gas plants restrictions. Ramp values were approximated to the data provided by Meibom et al. [53], and minimum power delivered to the grid was taken from reports by Ministry of Industry, Energy and Tourism, MINETUR [66, 67].

3.5.2 Scenarios definition

In this work, seven scenarios are considered, whose properties are summarised in table 3.2.

Scenario	Nuclear ramps	Fuel price	CO_2 price (€/t)	Hydro scenario	Hydro shadow price (€/MWh)	Wind production	Renewable production	Demand
1-Base	Historical	Average	51	Average	90	NREAP	NREAP	Base
2-Nuclear	REE	Average	51	Average	90	NREAP	NREAP	Base
3-High fuel	Historical	High	150	Average	165	NREAP	NREAP	Base
4-Low fuel	Historical	Low	26	Average	70	NREAP	NREAP	Base
5-Dry	Historical	Average	51	Dry	95	Low[1]	NREAP	Base
6-Humid	Historical	Average	51	Humid	85	High[2]	NREAP	Base
7-Low RW	Historical	Average	51	Average	90	Average [3]	Low [4]	Low

Note: this table is also presented as table E.9.

Table 3.2: Assumptions taken in the scenarios.

The main characteristics of the scenarios are explained below:

1. Base. It represents the reference case where the NREAP forecasts were assumed for the renewable production and demand. An average rainfall is considered and medium values are supposed for fuel prices and CO_2 emission taxes. Nuclear ramps values from historical data are assumed.

2. Nuclear. Identical considerations as in base case are taken except from the nuclear ramp values, which are faster; their values were deducted from the work by Atienza [68].

3. High fuel. In this scenario the fuel and CO_2 emission taxes are higher than in the remainder scenarios. NREAP forecasts were assumed for the renewable production and demand. An average rainfall was considered and historical values for nuclear ramps were taken.

4. Low fuel. In this case the fuel and CO_2 emission taxes are lower than in the rest of the scenarios. For the remainder parameters, identical hypotheses were assumed that in the high fuel scenario.

5. Dry. The rainfall considered in this case is lower than the average. With regard to the nuclear ramps, the historical values were taken. Medium values for fuel prices and emission taxes were considered. Wind power production was assumed lower than the average, and with respect to the rest of renewable production and the demand, NREAP hypotheses were assumed.

6. Humid. In this case rainfall is higher than in average years, and wind power yearly production is also larger. The remainder parameters were considered identical to those of the Dry scenario.

7. Low RW. Nuclear ramp values were taken from historical values. Regarding emission taxes and fuel prices medium worth was assumed. A hypothesis of an average rainfall was taken. The renewable installed capacity was computed taking into account that the assumptions of NREAP will not be met. Hence, the renewable production is lower than in the other scenarios. Along the same lines, future demand was calculated and resulted in lower values than in the rest of the scenarios, following the assumptions of economic

growth by International Monetary Fund [69], and the relationship between the demand and the economic growth.

Assumptions for all the scenarios are explained in depth in section E.3.3.

3.5.3 Results discussion

The results of the model for the seven proposed scenarios are presented in this section. Several parameters were analysed and some conclusions may be drawn, which will be presented below. These results are widely extended in E.3.4.

Daily market prices. The equilibrium equation in the daily market provides the marginal costs of the system. This parameter gives an idea of the rising cost of energy. In the considered scenarios, the price could significantly augment as it strongly depends on the fossil fuel prices. For the higher fuel price increase considered (high fuel scenario), the estimated price will augment up to 243 €/MWh, being the average price 164.09 €/MWh, while in the base scenario the average price will be 89.15 €/MWh. The price variability increases as the renewable energy share augments and the fuel prices rises. A lower rainfall could lead to a higher variability of the daily market price. Further results are presented in table E.17.

Yearly production by technology. In the base scenario, the increase in energy demand is supplied by renewable technologies (PV, CSP, biomass and wind power) and also by natural gas plants. In a scenario with rising emission taxes, such as the scenario high fuel (E3), the coal plants could dramatically decrease their production, because of their high emissions of greenhouse gases. In figure 3.3, productions by technologies using a determined fuel are represented for each scenario.

Capacity factor (CF). It is defined as the ratio between the annual production of a technology ($\sum E$) and the product of the installed capacity (P_{inst}) and the number of hours per year (n_h), and can be expressed as:

$$CF = \frac{\sum_{1}^{n_h} E}{n_h \, P_{inst}} \tag{3.5}$$

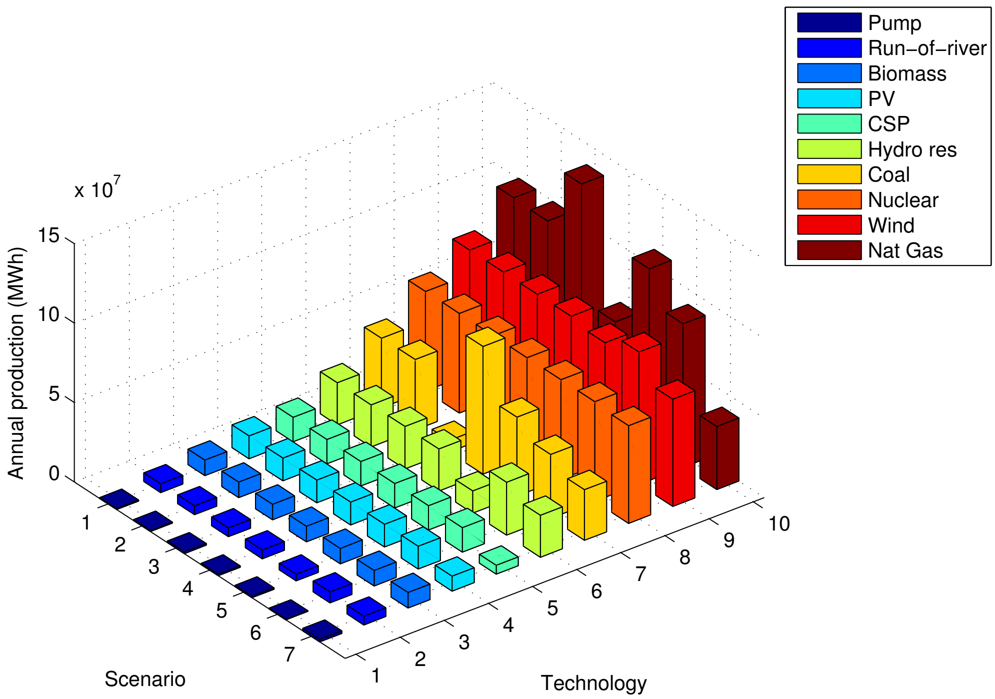


Figure 3.3: Production by technologies for the scenarios (MWh)

With regard to renewable technologies, biomass plants have the largest capacity factors, and technologies depending on sun, such as PV or CSP, have the lowest ones because of their limited operational hours. In a scenario with a high share of demand coverage by RES-E, the nuclear plants should operate in a more flexible mode in order to decrease the renewable energy shedding. The capacity factor of the hydro power will depend on the rainfall. Capacity factors of natural gas and coal plants are complementary to each other.

Wind shedding. The spilled wind energy due to excess of generation is computed in the proposed scenarios. The operation of more flexible nuclear plants could decrease the spilled wind energy in a system with high renewable energy share, from 107.2 GWh in the base scenario to 55.1 GWh in the flexible nuclear scenario. Moreover the higher the renewable energy penetration, the higher wind shedding, being 302 GWh in the Low RW scenario.

Net load. It is defined as the electric demand minus the effective renewable production, that is, deducting the wind shedding. Generally, net load is highly variable along the year, due on one hand to demand variations between peak and valley hours, and on the other hand to the overlap between these hours with low and high production of renewable energy. Values range between 1,200 and 55,000 MW. Results for net load of the different scenarios are depicted in figure 3.4. In Low RW scenario (7), since the demand decreases, net load also diminishes, although RES-E capacity is lower, in relative terms, renewable generation *versus* demand ratio (46%) increases with regard to the other scenarios (40% in the reference scenario).

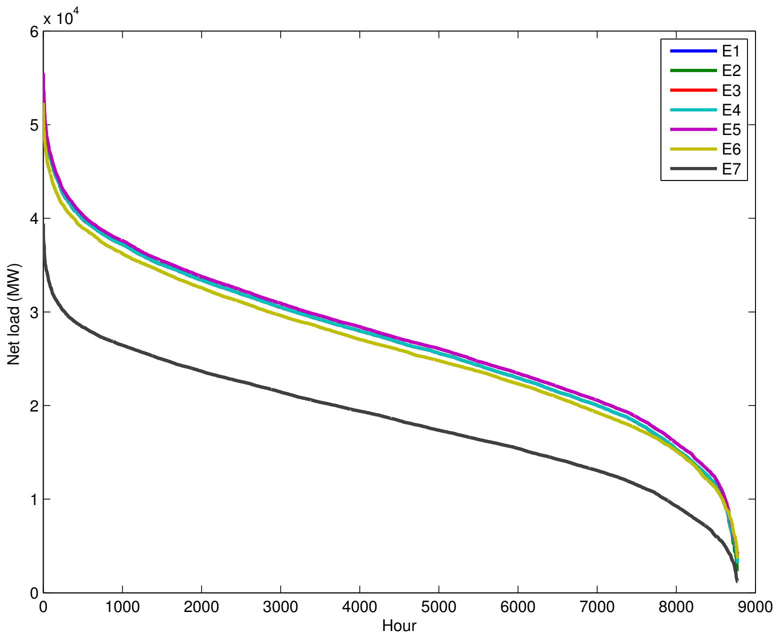


Figure 3.4: Net load duration curve.

Delta of net load. Another parameter to analyse is the variation of the net load from one hour to the next, which is called delta of net load. This variable gives an idea of the changes in the power output of the non-renewable portfolio of generators to deal with the variation of demand that they have to supply, and therefore this parameter gives an idea of their operation mode. Delta of net load increases with the installed renewable capacity. Therefore an increased penetration of renewable energy will require a more flexible portfolio of non-renewable plants. Figure E.22 represents the delta of net load.

Ratio of demand coverage from renewable sources. The duration curve of the demand coverage by RES-E is plotted in figure E.23. The renewable power does not match with the demand, and therefore the demand coverage is highly variable, oscillating from about 7% up to 95%.

Hourly variation of the hydro with reservoir power. These plants are operating some hours of the year that vary from 3,600 up to 5,400 hours depending on the proposed scenario. The hourly variation from one hour to the next oscillates from 7,500 to -5,000 MW. In this model these plants operate in a very flexible way, compensating the renewable production variation, because they are fast changing their power output.

Hourly variation of the natural gas power plants. These plants are less flexible than hydro with reservoir. The operation hours vary from 6,800 to 8,700 depending on the scenario, moreover their operation hours without power variation are about 4,000. The hourly variation oscillates between 2,800 and -2,500 MW, excluding the outliers which can reach values up to 7,000 MW when coinciding with peak demand. In the Low RW scenario (E7) the number of start-ups increase.

Hourly variation of the coal power plants. These technologies are operating during the whole year, except in the scenario high fuel, where the extremely high emission taxes entail a limited use of coal plants. The power output variation is lower than in the hydro power with reservoir and natural gas plants, with values varying from 2,200 MW to -2,000 MW.

$\mathbf{CO_2}$ emissions. In table 3.3 the CO_2 emissions of each scenario are presented. The higher emission levels take place in scenario Dry (E5), followed by Low Fuel and emission taxes scenario (E4). Conversely, the lowest CO_2 emission levels will occur in Low RW scenario (E7) because of the demand level diminution followed, by the humid scenario (E6). In conclusion, high emission taxes will lead to a lower emissions of the generation portfolio. The Kyoto protocol emissions limit is only met in E7, because of the lower demand and the relative demand coverage increasing by renewable energy.

Parameter	Base	Nuclear	High Fuel	Low fuel	Dry	Humid	Low RW
CO_2 emissions (Mt)	110	110	103	120	124	99	56

Note: this table is also presented as table E.19.

Table 3.3: CO_2 emissions per scenario.

Operation costs. Table 3.4 represents the disaggregated operation costs of all the scenarios. In a scenario of high emission taxes and fuel prices the operation cost will increase considerably. In the higher rainfall scenario the operation costs of the power system decrease with respect to the base scenario. In the case of Low RW scenario, operation costs diminish given that the demand is lower than in the other scenarios and, so, less plants using fuel are included in the generation mix.

Costs	Base	Nuclear	High Fuel	Low fuel	Dry	Humid	Low RW
CO_2 emissions (M€)	5587	5589	15427	3113	6266	5051	2853
CO_2 Start-up (M€)	26	25	65	15	56	22	17
Fuel (M€)	8442	8429	10420	7731	9291	7742	4573
Start-up fuel (M€)	45	45	40	53	33	40	33
Operation (M€)	14100	14088	25952	10912	15647	12856	7475

Note: this table is also presented as table E.20.

Table 3.4: Operation costs (M€)

3.5.4 Conclusions

The following conclusions may be extracted from the developed study:

- In a scenario with high emission taxes for greenhouse gases (GHG), combined cycle power plants displace coal plants.
- Capacity factors of power plants using fuels depend on both fuel prices and emission taxes of GHG. The higher the fuel prices and emission taxes of GHG, the lower the production of coal plants.
- A more flexible operation mode of nuclear plants, which includes a fast response to power output variations, leads to a decrease of wind power spillages.
- The installed capacity of RES-E technologies is related with the renewable shedding, so that the higher the penetration of RES-E technologies, the higher the renewable power spillages.
- Hydro with reservoir, coal and natural gas technologies operate in a more flexible mode in the presence of high penetration of RES technologies, including a more habitual use of severe operation ramps.
- In the considered scenarios, hydro plants with reservoirs habitually vary their power output to compensate the RES-E production variation. Second, natural gas plants frequently vary their power output and finally, coal plants occasionally change their power output to handle the RES-E power variation.
- Only in the scenario Low RW, assuming that demand slightly increases with respect to 2012 values and demand coverage by RES-E rises up to 46%, the Kyoto protocol would be met.
- In a scenario with high fuel prices and elevated emission taxes, operation costs would skyrocket.

Chapter 4

Conclusions

4.1 Conclusions

Taking into account the results presented in this work, some conclusions can be extracted.

With regard to the participation of a wind power producer in the Spanish power system the following conclusions can be formulated:

- Due to the uncertainties in wind power forecasting, imbalances strongly influence wind power revenues, and this implies a decrease in the wind farms economic benefits.

- The participation of wind power producers in intraday markets, through an strategic bidding process, improves their revenues. This process includes an optimization of the bid energy which takes into account the uncertainty of the variables involved in the problem. The optimal strategy described in this work includes deterministic intraday price forecasting as well as probabilistic power forecasting and probabilistic imbalance prices prediction from historical data. The strategy tends to sell more energy in the intraday market than forecasted, improving the incomes in that market although the imbalances between contracted and actual production increase.

- High volatility in prices is a characteristic of certain electricity markets with low liquidity. For the imbalance prices, this high volatility together with its random nature, make their modeling very complex, and hence imply important losses for wind power producers.

- A study has been made for nine wind farms spread in a wide area of the Spanish territory and in accordance to the Spanish market rules. In the mentioned study a non risk-constrained strategy is applied. In absolute terms the incomes increase. The proposed method improves the traditional one, that is, bidding the point prediction, in all the wind farms considered, leading to higher revenues for the wind power producer but also to a higher energy imbalance.

- Under the assumptions of the studied cases, when applying a risk management strategy in an optimization bidding strategy, the less severe the restriction is, the higher incomes are obtained, but an upper limit for the revenue can be established, which meets with the optimal strategy revenue. It is also shown that a decrease in the imbalance costs does not imply an increase in the revenues.

- The regulation of the imbalance prices may not be adequate for the Spanish electricity market because a power error drop is not sufficiently encouraged. The incomes obtained by the wind power producers are not completely correlated with their contribution to the overall power deviations. Indeed, in the test cases, higher deviations imply higher incomes.

- Alternative imbalance price schemes could enhance the reduction of deviations in the power system. Along these lines, we suggest the application of a new imbalance price scheme, which includes an additional constraint to avoid those cases in which deviations are not adequately penalised. Trying to prevent that the increase of benefits are based on price predictions instead of power predictions, when this suppose an increase of the deviations.

With regard to the study of the integration of renewable energies in the future Spanish power system, and under the hypotheses assumed in this work, the following conclusions may be extracted:

- In the proposed scenario with high emission taxes for greenhouse gases, combined cycle power plants displace coal plants.

- Capacity factors of power plants using fuels depend on both fuel prices and emission taxes of GHG. The higher the fuel prices and emission taxes of GHG, the lower the production of coal plants.

- A more flexible operation mode of nuclear plants, which includes a fast response to power output variations, leads to a diminution of wind power spillages.

- The installed capacity of RES-E technologies is related to the renewable shedding, such that the higher the penetration of RES-E technologies, the higher the renewable power spillages.

- Hydro with reservoir, coal and natural gas technologies operate in a more flexible mode in the presence of high penetration of RES-E technologies, including a more habitual use of severe operation ramps.

- In the considered scenarios, hydro with reservoirs habitually vary their power output to deal with the RES-E production variation. Second, natural gas plants frequently vary their power output and finally, coal plants occasionally change their power output to handle the RES-E power variation.

- Only in the scenario Low RW, in which the demand slightly increases with respect to 2012 values and demand coverage by RES-E rises up to 46%, the Kyoto protocol would be met.

- In a scenario with high fuel prices and elevated emission taxes, power system operation costs would skyrocket.

4.2 Contributions

This work includes the following contributions:

- The inclusion of a risk management analysis in a strategic bidding tool that entails deviation reductions by means of a stochastic optimization process.

- The proposal of a new cost-reflective imbalance pricing scheme.

- A model to estimate the future imbalance prices of the Spanish power system.

- A study of the Spanish power system in 2020, which includes an increasing installed capacity of RES-E.
- The implementation of a concentrated solar power module which determines the future production from radiation and characteristics of the installed capacity of this technology.

4.3 Future works

The work and results discussion presented in this document could be extended in the following fields:

- Optimising the concentrated solar power production, introducing the possibility of programming the production as a function of the demand requirements.
- Developing a stochastic study of the integration of renewable energies in the power system, which considers forecasting errors for wind power production, demand and reserves. On this study, a scenario reduction should be also implemented to make the problem tractable.
- Studying a 100% renewable generation scenario.

4.4 Published and presented papers

The results of this work have been published and/or presented in the following papers:

- Bueno, M., Moreno M.A., Usaola J. "Assessing the integration of wind energy producers in the Spanish electricity market". Proceedings of the INFORMS. Minneapolis (United States of America), October 2013.
- Bueno, M., Moreno M.A., Usaola J. "Analysis of the imbalance price scheme in the Spanish electricity market: a wind power test case". Energy Policy 62, 1010-1019 (2013).

- Moreno M.A., Usaola J., Bueno, M. "Assessing the economic benefit of a bidding decision support tool for wind power producers". IET Renewable Power Generation 7 (6), 707-716 (2013).

- Moreno M.A., Bueno, M., Usaola J. "Evaluating risk-constrained bidding strategies in adjustment spot markets for wind power producers". International Journal of Electrical Power & Energy Systems 43 (1), 703-711 (2012).

- Bueno, M., Moreno M.A., Usaola J., Nogales F.J. "Strategic Wind Energy Bidding in Adjustment Markets". Proceedings of the UPEC, Cardiff (United Kingdom), 2010.

- Usaola J., Rivier J., Sáenz de Miera G., Moreno M.Á., Bueno M. "Effect of Wind Energy on Capacity Payment. The Case of Spain". Proceedings of the 10th International Association for Energy Economics (IAEE) European Conference. Vienna (Austria), 2009.

- Usaola J., Moreno M.A., Sáenz de Miera G., Rivier J., Bueno M. "Impact of Wind Energy on Electricity Markets". Proceedings of the European Wind Energy Conference and Exhibition (EWEC 2009). Marsella (France), 2009.

4.5 Competitive projects participation

This work has been developed within the following competitive projects:

- "ANEMOS.PLUS (Advanced tools for the management of electricity grids with large-scale wind generation)". Funded by the European Commission (Research Directorate General). Reference: ENK5-CT-2002-00665. (01/01/2008-30/06/2011).

- "Integración de energías renovables en el mercado de electricidad". Funded by the Spanish Ministry of Science and Education. Reference: ENE2010-16074. (01/01/2011-31/12/2013).

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Appendix A

Strategic Wind Energy Bidding in Adjustment Markets

A.1 Abstract

The aim of the paper is to study the optimal participation of wind energy in adjustment markets in order to increase the wind producer revenues, through a stochastic optimization process, which considers the uncertainty of the random variables involved, namely short-term wind power prediction, intraday price prediction and imbalance price. A new modeling of the behavior of up and down imbalance prices in the Spanish market has been developed for this purpose. A comparison against different strategic biddings is included in order to show the income improvement, using as test case the participation of a wind farm in the Spanish electricity market over nearly a year.

A.2 Introduction

With the liberalization of electricity markets, wind power producers may dispatch their production through electricity pools and they must commit themselves for a production level in the settlement period. Their production is estimated by means of a forecasting tool. Although these tools have evolved rapidly in the last years, as reported by González et al. [6], Martí et al. [7], Pinson et al. [8], they still have a limited accuracy that leads to imbalance between the forecast and the actual production, and hence economic losses, as indicated by Fabbri et al. [9], Holttinen [10], Bathurst et al. [11]. The possibility of knowing the uncertainty of wind power prediction allows wind power participants in markets to optimize their position in order to maximize their revenue, as suggested by Usaola & Angarita [17], Pinson et al. [70].

Since the accuracy of forecasting tools depends, to some extent, on the time horizon of the prediction, updating bids in adjustment markets (shorter term) is profitable, as reported by Fabbri et al. [9], Holttinen [10], Angarita-Márquez et al. [16], Usaola & Angarita [17], Usaola & Moreno [18].

An important problem is the correct estimate of the imbalance prices, since they are difficult to forecast and the data are sometimes not available. Several authors have addressed this issue in different ways, such as, Holttinen [10] using real prices already known, Fabbri et al. [9], Matevosyan & Soder [20] reserve prices or Angarita-Márquez et al. [16] considering the average imbalance costs,but most studies performed up to now are a rough simplification of reality because they do not consider the uncertainty of the future imbalance costs, so that different results would be obtained under more realistic assumptions.

This paper addresses the optimal participation of wind energy in adjustment markets in order to increase the wind producer revenues, through a stochastic optimization process, which considers the uncertainty of the random variables involved, namely short-term wind power prediction, intraday price prediction and imbalance price prediction. Also the behavior of up and down imbalance prices in Spanish market has been modeled. The model follows a probabilistic approach which takes into account their stochastic character, and hence their uncertainties, and it has been integrated in the strategic bid generation, in order to minimize the imbalance costs and, in consequence, maximize the revenues for the wind producer.

The paper begins with a short introduction to wind power participation in electricity markets and short term wind power prediction. A prediction tool for prices in the intraday market and the model for the imbalance prices behavior follow. Then the formulation of the optimization strategy for bidding in an intraday market is included. Finally, the participation of a wind farm in the Spanish electricity market is simulated over nearly a year, illustrating the benefits of the new strategy in comparison to bids based only on point forecasts.

A.3 Wind Power in Electricity Markets

In many countries, electricity markets consist in a sequence of markets with different time scopes. Most transaction of energy are carried out in a Daily Market (DM), with commitments being made typically between 13 and 37 hours before the Operational Settlement Period (OSP). The Intraday Market (IM) is an adjustment market with shorter time scheduling and it may be continuous or be structured in several sessions, as in Spain. After every intraday market session, the system operator manages any deviations in real time using ancillary services and the deviation management procedure.

When wind energy participates in the electricity markets, it must interact in such a scheme. Since wind energy cannot be programmed in advance, it is necessary to have a prediction of the production for the next OSP, and the prediction should be available 24-48 hours before, with a rather acceptable reliability.

Normally, wind power producers participate in DM, committing themselves for the power predicted before the next gate closure. This means usually to make a bid for the DM and to update it in the IM, when predictions with lower errors are available. The imbalances are settled and paid at the imbalance cost. Since the accuracy of wind power predictions is not very high, imbalances are very important for wind power producers, and the imbalance price mechanism affects them especially.

A.3.1 Imbalance Costs

		SYSTEM REQUIREMENTS	
		LONG	SHORT
GENERATOR	LONG	min(SP,MP)	MP
PRODUCTION	SHORT	MP	max(MP,BP)

Table A.1: Dual price system scheme in the Spanish Market

There are two types of imbalance price mechanisms, as reported by ETSO [71]:

- Dual imbalance pricing, where a different price is applied to positive imbalance volumes and negative imbalance volumes; or

- Single imbalance pricing, where a single imbalance price is used for all imbalance volumes.

Where a dual imbalance pricing regime is followed, the main price is applied to imbalance volumes in the same direction as the overall market, whereas the reverse price is that applied to imbalance volumes opposite in direction to the overall market, e.g. “short” when the market is “long”, or vice versa.

The two price system scheme used in the Spanish electricity market may be represented in Table A.1, where MP means marginal price, BP buy price, and SP sell price.

A.3.2 Revenues of a Market Participant

The revenue R_t obtained by a wind farm participating in the electricity market in a settlement period t may be generalized as

$$R_t = P_{d,t}\pi_{d,t} + \pi_{i,t}(P_{i,t} - P_{d,t}) + IT_t \tag{A.1}$$

where $P_{d,t}$ and $P_{i,t}$ are the power committed to the wind farm for the period in the DM and IM, respectively; $\pi_{d,t}$ and $\pi_{i,t}$ are the marginal prices of energy in those markets and IT_t is the imbalance term for that period t, whose expression is

$$IT_t = \begin{cases} \pi_t^{sell}(P_{g,t} - P_{i,t}) & P_{g,t} > P_{i,t} \\ \pi_t^{buy}(P_{g,t} - P_{i,t}) & P_{g,t} < P_{i,t} \end{cases} \tag{A.2}$$

being $P_{g,t}$ the power actually generated by the wind farm in the period t, and π_t^{sell} and π_t^{buy} the imbalance price for overproduction (positive imbalance) and underproduction (negative imbalance), respectively.

Typically, $\pi_t^{sell} \leq \pi_{d,t} \leq \pi_t^{buy}$ and they may be written as

$$\begin{aligned} \pi_t^{sell} &= \alpha_t^{sell}\pi_{d,t} \\ \pi_t^{buy} &= \alpha_t^{buy}\pi_{d,t} \end{aligned} \tag{A.3}$$

with $\alpha_t^{sell} \leq 1$ and $\alpha_t^{buy} \geq 1$.advance.

A.4 Short Term Wind Power Prediction Uncertainty

Short term wind power prediction programs are tools that provide an estimate of the future power production of a wind farm, or a group of wind farms, for the next hours. For this purpose, they use meteorological forecasts coming from a Numerical Weather Prediction tool, and sometimes real time SCADA data from the wind farms, as wind power production, measured wind speed, etc. Data of the wind farms, such as rated power, type and availability of wind turbines, etc. are also necessary. The output of these programs is the hourly average wind farm production for the next 48 hours, with an accuracy decreasing with the time horizon. A survey of the accuracy of these tools is reported by Martí et al. [7]. All the prediction programs provide a *point prediction*, usually the expectation of the future wind production.

The predictions provided by a short term wind power prediction program are uncertain, and it is interesting to estimate this uncertainty in order to have more information about the future production of a wind farm. The probability density function (PDF) of this uncertainty is different depending on the range of the wind farm power output, since this value is bounded between zero and the rated power. The shape of these probability density functions is also affected by the time lag elapsed between the prediction and the operation times. Predictions with a shorter time lag are more accurate, and the variance of their uncertainty distribution is likely to be smaller than those predictions produced longer before. To obtain, analytically or in real time, the uncertainty of this prediction is not the aim of this paper. Instead, accurate estimations from past data will be used, such as by Usaola & Angarita [17]. Here, past predictions are compared with real production and tabulated, so that their frequency distribution may be used as an approximation of their probability density functions. Many of the nowadays short term wind power prediction tools provide already the uncertainty of the prediction produced.

A.5 Intraday Market Price Forecasting Tool

Nowadays, forecasting intraday electricity prices in competitive electricity markets is necessary for both producers and consumers in order to improve their market bidding strategies. This is specially important for the integration of wind energy into these markets, because producers can benefit from bidding in intraday markets to reduce their imbalance costs due to bids at the spot market.

There are some characteristics of electricity markets that affect the behavior of pool prices (Conejo et al. [72]). The fact that Electricity is non-storable, along with the insufficiently liquidity of markets, influence in a complex dynamic structure of electricity prices. Thus, it is necessary a careful analysis to such structure to provide us the relevant information for constructing an adequate model.

In this paper, the IM price forecasting problem is addressed through a time series model. It is assumed that there is one daily market and I intraday market sessions, each one with t_i hours.

Typically, forecasting for day D in the daily market must be done on day $D-1$, around 10 am, and forecasting for each i-th IM session must be done around three hours before the beginning of such market. Moreover, to forecast prices for the i-th intraday market in day D, price data up to the $(i-1)$-th intraday market and the daily one are considered known.

The model has been obtained using the following three-step process:

- Step 1. Several transformations are applied to the original series to obtain stationary ones. Then, a time series model is identified for each intraday price, $\pi_{i,t}$.

- Step 2. All parameters for each intraday models are estimated, as well as the parameters of the error noises.

- Step 3. A diagnosis check is used to validate model assumptions. If the hypotheses of the model are validated, the procedure concludes and the model is ready for forecasting; otherwise the procedure continues in Step 2 to redefine the model.

Then, the model to forecast IM price at hour t for each of the i-th session, $\pi_{i,t}$, can be formulated in following way:

$$\log \pi_{i,t} = c_i + \phi_{1,i} \log \pi_{i,t-1} + \phi_{2,i} \log \pi_{i,t-2} + \\ + \phi_{i,24} \log \pi_{i,t-24} + \beta_{i-1,i} \log \pi_{i-1,t} + \beta_{2,i} \log \pi_{d,t} + a_{i,t} \quad \text{(A.4)}$$

where $a_{i,t}$ is a noise term with a $N(0, \sigma_i^2)$ distribution for all t, and c_i, $\phi_{t,i}$ and $\beta_{t,i}$ are the model parameters for each intraday market i and hour t.

A.6 Uncertainty of Imbalance Prices

The imbalance prices in an electricity market are highly variable and difficult to forecast. They are, however, very important for a wind producer, because of the today unavoidable imbalance between scheduled and generated energy. Actually, in the Spanish power system, wind generators are the source of much of the whole system imbalance, as can be found in the study by Red Eléctrica de España [32].

Imbalance prices have also high volatility, since the number of participant and the amount of energy exchanged are relatively low, and (in dual pricing systems) because of the random nature of the overall imbalance system.

For all these reasons, modeling of imbalance prices is very complex. Many studies, such as Usaola & Moreno [18], have been made to assess the wind power producer imbalance losses with strategic bidding (see below), but these results were too optimistic since most of them assumed an average or fixed imbalance price, and did not considered their high volatility.

In this paper, a proposal for modeling these imbalances is made, in order to prepare strategic bidding aiming at minimizing the imbalance costs for a wind producer.

In order to assess the behavior of imbalance prices, and to develop a heuristic approach to their forecast, the values of imbalance prices for each hour of the day throughout the year 2007 were collected. Results are represented in Fig. A.1 and Fig. A.2, where π^{buy} and π^{sell} are buy and sell prices respectively. In the graphs, the central mark is the median, the edges of the box are the 25% and 75% percentiles, the whiskers extend to the extreme data, without outliers, and outliers are plotted individually. A high variability of these prices can be observed, but also a shape pattern is apparent.

From this study, the following conclusions may be made:

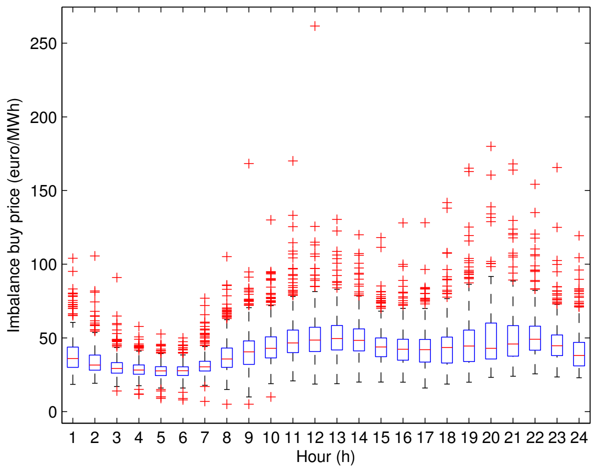

Figure A.1: π^{buy} boxplot for hourly trends analysis.

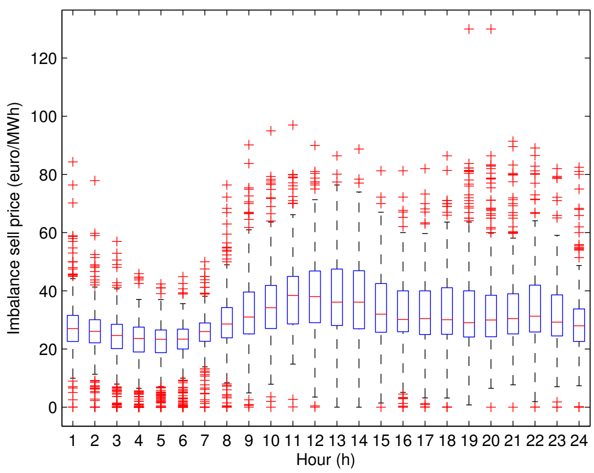

Figure A.2: π^{sell} boxplot for hourly trends analysis.

- The imbalance prices follow a daily pattern. This is valid both for sell and for buy prices.
- A statistical parameter may be adequate as an estimate of the imbalance price. After several trials, the results obtained with the mean were the best.
- The frequency distribution shown in the graphs may be regarded as a first approach to the PDF of imbalance prices distribution.

The model of uncertainty proposed here, and implemented in the optimization process described below, consists in using the values of imbalance prices from the previous three months to obtain an approximation of their PDFs. Besides, instead of the prices themselves, the parameters α_t^{sell} and α_t^{buy} have been actually used.

A.7 Optimal Bidding Strategy

The imbalance losses for a wind power producer are significant, and may be reduced by strategic bidding. This strategic bidding uses the uncertainty of the wind power predictions and imbalance prices, and arbitrages between expected prices of energy in intraday markets and expected imbalance costs.

The problem considered here is the optimization of the bid to the IM, given a position in the DM, and taking into account the uncertainties of the involved random variables.

Under these conditions, the revenue R_t obtained by a wind farm participating in the electricity market in a settlement period t is a random variable that depends on other random variables, namely the power production $P_{g,t}$, the IM price $\pi_{i,t}$, the buy price coefficient α_t^{buy} and the sell price coefficient α_t^{sell}. The aim of the problem is to obtain the bid in the IM, $P_{i,t}$, that maximizes R_t. Since the optimization problem is independent for each time t, this subscript will be omitted from now on.

If $R = g(P_g, \pi_i, \alpha^{sell}, \alpha^{buy}; P_i)$, where g is given by (A.1), and P_g, π_i, α^{sell} and α^{buy} are considered independent random variables, the probability density function f of the random variable R is

$$f(R) = f(P_g, \pi_i, \alpha) = f_{P_g}(P_g) f_{\pi_i}(\pi_i) f_\alpha(\alpha) \tag{A.5}$$

where $f_{P_g}(P_g)$ and $f_{\pi_i}(\pi_i)$ are the probability density functions of the random variables P_g and π_i, and $f_\alpha(\alpha)$ may be developed as:

$$f_\alpha(\alpha) = \begin{cases} f_{\alpha^{sell}}(\alpha^{sell}), & P_{g,t} > P_{i,t} \\ f_{\alpha^{buy}}(\alpha^{buy}), & P_{g,t} < P_{i,t} \end{cases} \tag{A.6}$$

Hence, the expected revenue will be

$$\begin{aligned} \overline{R} = E\left[R; P_i\right] = \\ = \iiint_{-\infty}^{\infty} g(P_g, \pi_i, \alpha; P_i) f(P_g, \pi_i, \alpha)\, dP_g\, d\pi_i\, d\alpha \end{aligned} \tag{A.7}$$

and the optimization problem can be posed as

$$P_{i,opt} = \arg\max_{P_i} E\left[R; P_i\right] \tag{A.8}$$

with $P_{i,opt}$ being the optimal position to be taken in the IM. This problem may be discretized and solved easily by simple enumeration, and it must be solved for each time t.

A.8 Study Cases

In order to assess the performance of the proposed method, a test case has been prepared following the rules of the Spanish electricity markets, where participation of wind energy is possible and it is encouraged by a subsidy. The assumptions followed in the study are:

- The market is a pool with marginal prices. This is valid both for the daily market and for the adjustment (intraday) markets.
- Wind producers make their bids for a given amount of power at price zero and bids are always accepted.
- Prices in the intraday market do not depend on the amount of wind power bid (the IM is sufficiently liquid).
- Subsidies for wind energy are not considered.

In this context, it is assumed that only an update is made for each hour in the corresponding IM market, once energy bids are presented to the daily market. For each hour, energy bid updating is made in the next IM. Thus, the schedule for the update of bids for day D is made following the rules of Table A.2, which follows those of the Spanish electricity market (OMEL [33]). In it, the daily market has its gate closure at 10h, and therefore the bids for the daily market have a lead time between 14 and 37 hours. The lead time for the six existing intraday markets spread throughout the day varies from 3-4 hours until 5-8 hours.

The data of wind farm used in the simulation studies come from the actual production of a wind farm during a period of nearly a year. The PDFs of the

Hour	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
IM session	2				3			4				5				6					1 (D+1)			

Table A.2: Rules for updating energy bids for day D in intraday markets.

wind power predictions uncertainty have been obtained from production data and predictions performed for this wind farm for this period of time.

Historical data of intraday and imbalance prices of the Spanish market have been used to forecast the imbalance prices and to estimate the imbalance costs using the model developed, respectively. Prices of the Spanish electricity market may be obtained from OMEL [33] and E-sios [34].

The study performed includes a comparison between three different bidding methods:

1. Reference case, which consists in bidding to the market the point prediction of wind power. This method leads to the lowest error between prediction and production.

2. Fixed-α case, in which the uncertainty of the short term wind power prediction is taken into account to make a strategic bid. Hence, the value of $P_{i,opt}$ that maximizes the expected revenue is bid in the market. IM prices are forecasted as previously shown and the imbalance prices are estimated through a fixed value, namely the mean of their distribution (i.e. coefficients α^{buy} and α^{sell} are constant throughout the period).

3. Hourly-α case, that tries also to maximize the revenues, but including also the uncertainties of the imbalance prices in the optimization method.

A.8.1 Reference case

Based on the historic data, through a point prediction method, a standard method is developed so as to forecast the future power production for the wind producer.

In the reference case, the bid is made with the last prediction available at gate closure time.

	NMAE	MEDAPE
Error(%)	11.57	8.21

Table A.3: IM Price prediction tool accuracy

A.8.2 Fixed-α case

The PDF of the wind farm production has been obtained from the production data and predictions for the year 2007, following the methodology described in section A.4. A probabilistic approach was developed in order to obtain the prediction and its uncertainties, which are considered in order to calculate the optimal bids. This last type of uncertainty estimates are associated to a probability related to the likeliness of future power production.

Whatever their nature, such uncertainty estimates are expected to be valuable for developing alternative strategies for the management or the trading of wind power generation. In a general manner, they are necessary for optimizing the decision-making process related to the use of wind power forecasts.

IM prices have been forecasted using the tool described in section A.5. The accuracy of the tool was evaluated to determine its expected error. For this purpose, two parameters were selected: the Median Absolute Percent Error (MEDAPE), which was selected because of its better performance in presence of zero prices, and the Normalized Mean Average Error (NMAE), which was normalized with the average value of IM prices in year 2007. After the execution for a period of almost a year, the values of both parameters are shown in Table A.3. From both values, it can be concluded that the IM prices prediction tool has a good accuracy.

A first approach taking into account the uncertainty of forecast tool was carried out, but this strategy did not improve the revenues for the wind power producer and then the uncertainty of forecasted IM prices is not be considered in the optimal bid calculation from now on.

In order to use realistic values for the imbalance prices, the average yearly values from the Spanish market in 2007 have been selected, as in Usaola & Moreno [18]. Then, coefficients α^{sell} and α^{buy} are 0.8 and 1.1, respectively, and uncertainties of imbalance prices are not considered.

Since the only uncertainty included is that of the wind power production, the

	α^{est}	α^{known}	ΔR (%)
Revenue(€)	1,397,400	1,461,800	4.61

Table A.4: Comparison between perfect and estimated value of Imbalance Price

objective function shown in (A.7) can be simplified as

$$\overline{R} = E\left[R; P_i\right] = \int_{-\infty}^{\infty} g(P_g; P_i) f(P_g)\, dP_g \tag{A.9}$$

The revenues obtained with this strategy have been compared to those obtained assuming a perfect knowledge of imbalances prices, in order to quantify the economic costs due to imbalances. Results are shown in Table A.4, where α^{est} represents the average value of α_t^{sell} and α_t^{buy} in the year 2007, and α^{known} means that real values of imbalance prices were taken. The revenues presented were obtained for a simulation time of almost a year (305 days) and it shows that a better estimation of imbalance prices might improve the revenues up to a 4.61%.

A.8.3 Hourly-α case

Taking into account the previous results, the estimate of imbalance prices has been improved and their uncertainty has been considered by means of a hourly PDF from the imbalance prices of the previous three months to IM closure, as described in A.6.

Besides, since the uncertainties of forecasted IM prices are not considered, the objective function shown in (A.7) may be simplified:

$$\overline{R} = E\left[R; P_i\right] = \iint_{-\infty}^{\infty} g(P_g, \alpha; P_i) f(P_g, \alpha)\, dP_g\, d\alpha \tag{A.10}$$

A.8.4 Results comparison

The several bidding strategies were evaluated during almost a year (305 days). The results of the implementation are presented in Table A.5, where the revenues for the wind producer following the different strategies explained before may be compared. The average power error and the average of the absolute power errors,

Table A.5: Total revenue and errors for the different strategies

	Hourly-α	Fixed-α	Reference case
Revenue (M€)	1.4028	1.3974	1.3924
Power error (MW)	0.8061	0.8015	0.0940
Abs. power error (MW)	3.0677	3.1686	1.7874

in MW, are also shown in the table. These errors were calculated, for each hour t, as

$$\begin{aligned} \textit{Power error}_t &= P_{i,t} - P_{g,t} \\ \textit{Absolute power error}_t &= |P_{i,t} - P_{g,t}| \end{aligned} \tag{A.11}$$

From results in Table A.5, it may be said that:

- The prediction power tool has a trend to overprediction, as it may be deduced from the positive value of power error.
- Optimal strategies improve the revenues although the power error increases.
- This error is similar for both optimal strategies, but to include the uncertainties of imbalances prices leads to a lower absolute power error.

Although it has been demonstrated the importance of a good estimation of the imbalance prices for wind producers, the increase in revenues is only of a 0.74% over the reference case. This is due to the high volatility of imbalance prices at certain hours in a day. As an example, the values of α^{sell} and α^{buy} at hour 11 throughout the year 2007 are shown in Fig. A.3. Though a prevailing value could be appreciated, the atypical values are the cause of unexpected imbalance losses (it should be noted that some points take four times the marginal price value). Also a high dispersion can be appreciated in the figure.

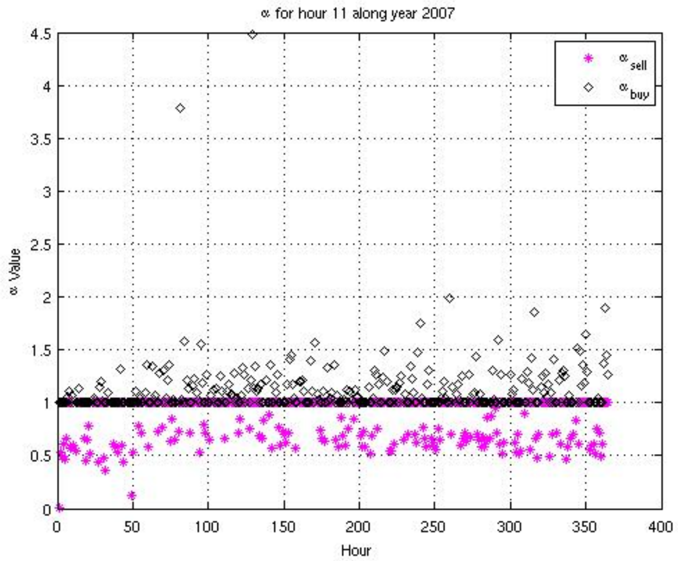

Figure A.3: Representation of α_t^{buy} and α_t^{sell} at hour 11 in 2007.

A.9 Conclusion

From the simulations run, and under the assumed hypothesis, the following conclusions may be drawn:

- Due to the uncertainties in wind power forecasting, the imbalances influence strongly in wind power revenues, and this implies a decrease in their economics benefits.

- Integration of intraday price forecasting in strategic bidding improves revenues for wind power producers.

- An adequate estimate of imbalance prices leads to an increase in revenues for a wind participant. Two ways of estimation have been tested in the paper, and their results have been compared with those of the usual strategy based on point predictions.

- High volatility in prices is a characteristic of certain electricity markets with low liquidity. For the imbalance prices, this high volatility together with its random nature, make very complex their modeling, and hence important losses for the wind power producers.

- In order to minimize these losses, further studies are needed trying to integrate a management risk strategy for imbalance costs.

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Appendix B

Evaluating risk-constrained bidding strategies in adjustment spot markets for wind power producers

B.1 Abstract

Participation of wind energy in the day-ahead electricity market implies large deviations from the initial schedule, which leads to costs for the wind farm owner. By means of short-term wind power prediction programs, the contracted energy can be updated in adjustment spot markets, reducing the power deviations and increasing the total revenue for wind power producers. Taking into account the different uncertainties involved in the problem, an optimal bidding strategy can be used to maximize the wind power producer revenues. As the strategy could be very risky due to all these uncertainties, a CVaR constraint for the bid that maximizes the expected revenue is proposed as a way of reducing the risk. A test-case using the Spanish market rules during a 10-month period has been used to check the potential benefits of the aforementioned strategies.

B.2 Introduction

Since the liberalization of the electricity markets, the integration of wind power in the electric energy systems has increased in many countries, and wind producers participate in electricity markets trying to maximize their benefits. This participation implies following the energy market rules and, in general, wind power producers commit a production level, which must be delivered in the settlement period as in Singh & Erlich [73]. As wind power is intermittent and un-dispatchable, the future production is estimated through a short-term wind power prediction tool, and there is always an imbalance between the scheduled and the actual production. The wind producer must then buy or sell the difference in the balancing markets, leading to economic losses, since this energy is traded in worse conditions than in the spot energy markets.

One way of reducing the error prediction costs is updating the bid made to the day-ahead market in adjustment markets, when predictions with shorter horizons, and thus higher accuracy, are available, as reported in studies by Fabbri et al. [9], Holttinen [10], Angarita-Márquez et al. [16], Usaola & Angarita [17], Usaola & Moreno [18], Bourry & Kariniotakis [19].

The losses can also be reduced considering the uncertainty of the forecasts, in an optimization strategy which bids a given power to the electricity market, trying to reduce the economic losses, and consequently, improve the revenues. Several approaches for the uncertainty estimation can be found in literature, such as Usaola & Angarita [17], Pinson et al. [70, 12], Monteiro et al. [13], Nielsen et al. [14], Pinson et al. [8], Morales et al. [15]. These optimization strategies are commonly used to foster the incomes of generation producers as in Bompard et al. [74].

Another way of reducing the imbalance costs is the combination of wind energy with an Energy Storage Device, as reported by Wang & Yu [75], Dukpa et al. [76] or hydro plants by Jaramillo Duque et al. [77]. These methods optimize the benefits of a coordinated participation in the electricity market, decreasing the losses due to uncertain forecasts.

But market participants must also cope with uncertain market prices. Then, a prediction of the electricity prices is a goal in most optimization problems, as shown in Pousinho et al. [78], Vilar et al. [79], Nabona & Pagès [80], Lotfi & Ghaderi [81], Dent et al. [24], Muñoz et al. [82]. Specially relevant is the estimate of the imbalance prices, because the deviations between committed and delivered power are paid according to these prices and lead to imbalance costs which must be borne by the wind power producers. A bad model of these prices may influence strongly the revenues obtained. Since it is not possible to know in advance the value of the imbalance prices, several authors deal with this issue using known prices as in Holttinen [10], considering reserves prices, such as by Fabbri et al. [9], Matevosyan & Soder [20] or employing average imbalance prices (Usaola & Moreno [18], Dent et al. [24]). All these studies are based on simplifications of reality, because the uncertainty of the future imbalance prices and their high dispersion are not considered, so the results obtained may widely differ from those obtained with more realistic assumptions. Further advances in a more proper modeling considering actual imbalance prices were presented by Bueno et al. [1].

A risk management restriction may be included in the optimization strategy in an effort to reduce the hazard of having extremely high imbalance losses. This kind of methods considers either the variability of imbalance prices, such as Dicorato et al. [21], Jabr [83], or the production uncertainty risk (Botterud et al. [22], Dent et al. [24]), or both (Morales et al. [15], Pousinho et al. [84]), and handles them in order to increase the revenues obtained by the wind power producer with minimum risk.

This paper addresses the optimal participation of wind energy in adjustment *spot* markets[1], or intra-day markets, in order to increase the wind producer revenues, through a stochastic optimization process which considers the uncertainty of the random variables involved, namely short-term wind power prediction, intraday market price prediction and imbalance price prediction. Historic market prices are used to forecast future prices in the adjustment markets and a probabilistic approach, also based on historic imbalance prices, is considered to estimate the future imbalance prices, taking into account their stochastic character. To deal with extremely high and no predictable imbalance prices, a management risk constraint is integrated in the optimization strategy aiming to maximize the profit and reduce the risk of high losses. The strategies presented in this paper are different from those of previous literature.

In order to evaluate the actual performance of the proposed trading strategies, the participation of a 21 MW wind farm in the Spanish electricity adjustment markets during a period of 10 months is considered. Results are compared with those obtained with bids based only on point forecasts.

[1] The European convention is adopted in this article; in the USA the term *forward markets* is used.

Compared to previous works, this paper presents new contributions. It includes an estimate of imbalance prices based on real data and not hypothetical scenarios, and the wind power forecasts are produced with a prediction tool in comparison to theoretical models of wind scenarios presented in other works. In short, all data considered in this paper are based on actual data (market prices, power productions and wind power forecasts). Also, an approach to reduce the risk in the participation of wind traders in electricity markets has been developed. This analysis comprises both production volume and volatility prices risk which are computed in a very simple and efficient way. A wide range of different risk levels is also included in this paper, allowing us to model different attitudes towards risk. Furthermore, the method deals with an analysis for ten months, which includes data affected by seasonality. This mathematical problem takes into account the participation in three electricity markets, namely, day-ahead, adjustment and imbalances, and involves the uncertainties of both wind power production and electricity prices. The solution is obtained by a simple procedure, which is easy to embed in a real time decision-making tool, because it simulates the standard procedure of wind traders in the Spanish electricity market. This paper also presents conclusions that could be useful for market participants, relative to risk-constrained optimization strategies.

Summarizing, the main contributions of this paper are to provide:

1. A probabilistic model of imbalance prices, which allows considering imbalance prices uncertainty in bidding strategies for wind power producers.

2. An effective and simple way to improve the profit of wind power producers through an optimization procedure.

3. A new strategy for the risk-constrained participation in adjustment markets, considering a CVaR value associated to both volume production and market prices variability. The attitude to the risk of wind traders is modeled in this work.

4. A thorough analysis for almost one year of data, so that the advantages of different strategies can be assessed.

The paper begins with a short introduction to wind power participation in electricity markets and short-term wind power prediction. Uncertainty of market prices is considered in Section B.5 where a probabilistic approach for estimating imbalance prices is described. The optimal strategy for bidding in adjustment spot markets is formulated in Section B.6 as an optimization problem, which aims at maximizing the expectation of the revenues for the wind power producer. The optimal risk-constrained strategy is included in Section B.7. Section B.8 describes the test-case used to check the performance of the new trading strategies and results are provided in Section B.9 in comparison to a point forecast trading strategy. Finally, the main conclusions of the study are presented in Section B.10.

B.3 Wind power in electricity markets

The electricity market is composed by a set of different sub-markets, with several schedule horizons. Most of the energy negotiated in a pool is traded in the day-ahead market, or Daily Market (DM), where the commitment is made usually the day before the Operation Settlement Period (OSP). The Intra-day Market (IM) is an adjustment market with shorter time scheduling, which may be continuous, as the Elbas Market, or structured in several sessions, as the Spanish Market. Previous studies by Weber [30] have shown the advantages of the actual market design of the Spanish Market to enable the integration of wind energy into the power systems.

After every IM session, the system operator solves the real time deviations, making use of ancillary services and the following deviation management procedure.

If wind power producers participate in the electricity market, they must interact in such scheme. Consequently, trading wind energy in the day-ahead market requires forecasts of future wind generation for horizons up to typically 2 days ahead (for the next OSP) with an admissible reliability.

These forecasts may be updated in the intra-day markets, with shorter times between the gate closure and the start of the energy delivered period, and therefore, more accurately. In spite of this, forecasting errors do exist, and differences between contracted and actual energy production will be produced, causing imbalances for the power system. These differences have to be settled in the deviation market procedure at the imbalance prices, usually leading to important imbalance costs for wind power producers. For example, wind power is the technology causing the most imbalances in the Spanish system (about 28% of the overall imbalance in 2010), only exceeded by demand, as reported by Red Eléctrica de España (REE) [85].

B.3.1 Imbalance pricing

Due to the importance of the imbalance prices for wind power producers, a short description of two existing pricing mechanisms are briefly described in ETSO [71]:

- Dual imbalance pricing, where a different price is applied to positive imbalance volumes and negative imbalance volumes; or

- Single imbalance pricing, where a single imbalance price is used for all imbalance volumes.

Most pricing mechanism follow dual imbalance pricing, where the main price is applied to imbalance volumes in the same direction as the overall market, whereas the reverse price is applied to imbalance volumes opposite in direction to the overall market e.g. *short* when the market is *long*, or vice versa.

The two-price system scheme is represented in Table B.1, where the main price is the day-ahead marginal price (*MP*) and the reverse prices are *BP* (buy price) or *SP* (sell price), depending on the sign both of the system imbalance and the producer imbalance.

		SYSTEM REQUIREMENTS	
		LONG	SHORT
GENERATOR PRODUCTION	LONG	*SP*	*MP*
	SHORT	*MP*	*BP*

Table B.1: Dual imbalance pricing scheme.

Reverse prices are less profitable for the producer than main price, to avoid arbitrage opportunities. They satisfy $SP \leq MP \leq BP$. When there is an excess of generation in the system (market long), an excess of production is usually paid at a lower price than the day-ahead marginal price, and when there is a deficit of generation in the system (market short), those participants responsible for the system imbalance must usually pay their imbalance at a higher price.

From Table B.1, it is remarkable that only those participants contributing to the system imbalance are penalized.

B.3.2 Revenues of a market participant

Let us consider the following assumptions about the participation of wind power producers in markets:

- The electricity market is a pool with marginal prices. This premise is valid both for the daily and intra-day markets.
- The wind power producer bids will be always accepted, offering them at zero price, if selling energy, and at the maximum price, if buying energy in the adjustment market.
- The quantity of energy bid by the wind power producers does not influence the intra-day market price. This statement is not completely realist, as liquidity may influence the final results[2], but Spanish intra-day market, which motivates this work, can be considered liquid enough as reported by Weber [30], so that it is a good choice for adjustment markets in systems with high wind penetration.
- Hourly power committed at the day-ahead market is updated only once in the adjustment market.
- Wind power subsidy will be not considered in the revenue of wind power producers. This fact will not influence the final results.

Under these conditions, the revenue R_t obtained by a wind farm participating in the electricity market in a settlement period t may be generalized as

$$R_t = P_{d,t}\pi_{d,t} + \pi_{i,t}(P_{i,t} - P_{d,t}) + IT_t \tag{B.1}$$

[2] As the intra-day markets have less liquidity than the day-ahead market, some problems may appear with the participation of large amounts of wind power in them (wind power producers may participate in the intra-day market buying or selling energy at the same time). This impact of large amounts of wind power in the intra-day market is still to be evaluated and it is not considered in this work.

where $P_{d,t}$ and $P_{i,t}$ are the power committed by the wind farm for the period t in the DM and IM, respectively; $\pi_{d,t}$ and $\pi_{i,t}$ are the marginal prices of energy in those markets and I_t is the imbalance income resulting from the balancing process for that period t, given by

$$IT_t = \begin{cases} \pi_t^{sell}(P_{g,t} - P_{i,t}),\ P_{g,t} \geq P_{i,t} \\ \pi_t^{buy}(P_{g,t} - P_{i,t}),\ P_{g,t} < P_{i,t} \end{cases} \tag{B.2}$$

being $P_{g,t}$ the power actually generated by the wind farm in the period t and π_t^{sell} (π_t^{buy}) the imbalance price for overproduction (underproduction).

It can be said that $\pi_t^{sell} \leq \pi_{d,t} \leq \pi_t^{buy}$, according with the dual imbalance pricing described before, and reasonable assumptions are

$$\pi_t^{sell} = \alpha_t^{sell}\pi_{d,t} \tag{B.3}$$

$$\pi_t^{buy} = \alpha_t^{buy}\pi_{d,t} \tag{B.4}$$

with $\alpha_t^{sell} \leq 1$ and $\alpha_t^{buy} \geq 1$.

Then, the imbalance income term may be expressed in function of ratios α as

$$I_t = \begin{cases} \alpha_t^{sell}\pi_{d,t}(P_{g,t} - P_{i,t}),\ P_{g,t} \geq P_{i,t} \\ \alpha_t^{buy}\pi_{d,t}(P_{g,t} - P_{i,t}),\ P_{g,t} < P_{i,t}. \end{cases} \tag{B.5}$$

B.4 Short-term wind power forecast uncertainty

The short-term power forecasting programs are tools which provide an estimate of the expected production of a wind farm in the near future. In order to provide these forecasts, numerical weather prediction programs and real time SCADA data, such as measured wind speed, wind power production, etc., are usually employed. In addition, to obtain the forecasts, some characteristics of the wind farm should be known, such as nominal power, type and availability of turbines, etc.

Many of the forecasting programs provide a deterministic prediction, or *point prediction*, i.e., a single value for each look-ahead time, which corresponds to the expectation or most-likely outcome. Furthermore, some forecasting tools can estimate the uncertainty of the forecasts, that is, the probability of having a production different from the expected value. This uncertainty gives additional information about the future wind power production.

The probability density function (PDF) of the uncertainty depends on the production level (between zero and the nominal power of the wind farm) and the time horizon, among other factors as Martí et al. [7] points out. Predictions with a shorter time lag are more accurate, and the variance of their uncertainty distribution is likely to be smaller than those predictions produced longer before. To obtain an estimate of this uncertainty is not the aim of this paper and the same approach used by Usaola & Angarita [17] has been followed: the range of historic predictions and observations of a wind farm production is split into several sub-ranges in order to obtain their frequency distribution, which will be employed as an approximation of their PDF. Better approaches may be made, but this issue falls beyond the scope of this paper.

B.5 Uncertainty of market prices

The participation of wind energy producers in electricity markets implies forecasting the future market prices. In the problem considered in this paper, there are three uncertain market prices: the day-ahead marginal prices (DM prices), the intra-day market marginal prices (IM prices) and the imbalance prices. As this paper deals with an optimal update of bids in the intra-day market, DM prices will be known by the time of bidding in the IM, and thus the only uncertain market prices considered in this work are IM prices and imbalance prices.

The methods used in this paper to forecast or estimate these prices are described in the following subsections.

B.5.1 Intra-day market price forecasting

The characteristics of electricity markets influence the behavior of market prices, but in general, the electricity prices possess a complex dynamic structure with non constant mean and variance, high frequency and volatility, presence of outliers, daily and weekly seasonality and calendar effect on weekends and holidays, which makes them hard to forecast, as Nogales et al. [86] indicates. Regarding the IM, the lower liquidity of that market makes the forecasting of electricity prices even harder and a careful statistical analysis must be done in order to construct a suitable model.

Assuming the structure of the Spanish electricity market, the IM price forecasting issue is dealing in this work with a time series model, as explained by Bueno et al. [1]. Forecasting for each IM session in day D must be done at least three hours before the beginning of such session. Then, DM prices and IM prices for the previous IM session are known and can be used as inputs to the model, obtaining forecasted prices for the next IM session.

The forecasting tool can also compute the uncertainty of the forecasts through probability density functions associated to each one.

B.5.2 Uncertainty of imbalance prices

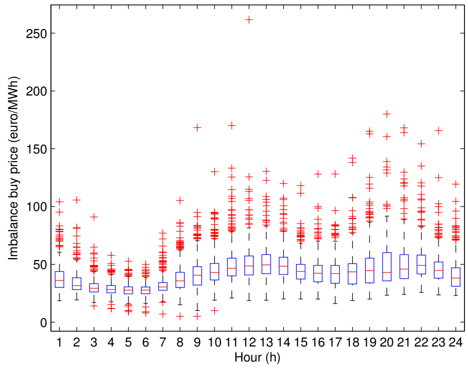
Imbalance prices have also high volatility, since the number of participants and the amount of energy exchanged are relatively low, and, in dual pricing systems, because of the random nature of the overall imbalance system. Modeling of imbalance prices is thus very complex, and previous works considered an average or fixed imbalance prices without taking into account their high volatility and their uncertainty. In this paper, a probabilistic model is included which takes into account this uncertainty through probability density functions developed with an heuristic approach.

In order to assess the behavior of the imbalance prices, the hourly values of imbalance prices (sell and buy) throughout the year 2007 were collected from E-sios [34] and classified into 24 classes, one for each hour of the day. The values into each class are shown in Figure B.1 using a box plot.

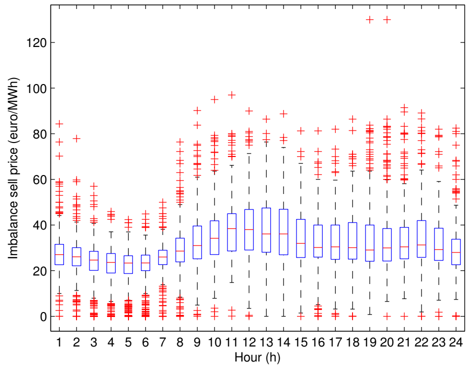
A high variability of these prices can be observed, but also a different behavior for each hour of the day. Moreover, a shape pattern remembering the daily demand curve is apparent.

Also the ratio between the imbalance prices and the DM prices (coefficients α_t^{sell} and α_t^{buy} in (B.3) and (B.4)) have been represented for each hour of the day in Figure B.2, showing a greater variability for α^{buy} than for α^{sell}, as α^{buy} ranges from 1 to 6 whereas α^{sell} does from 0 to 1.

From the daily distribution of the imbalance prices (sell and buy prices), a different model for the imbalance price in each hour of the day may be inferred. Also, the frequency distribution shown in the graphs may be regarded as a first approach to the PDF of the imbalance price distribution.

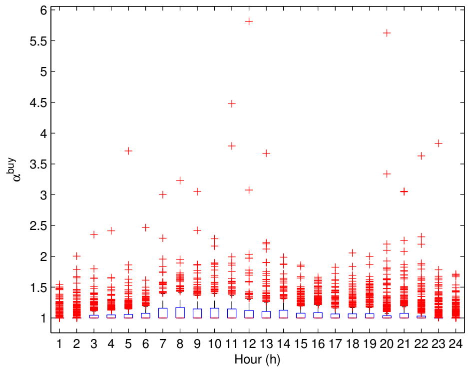


(1) Box plot of π^{buy} in each hour.

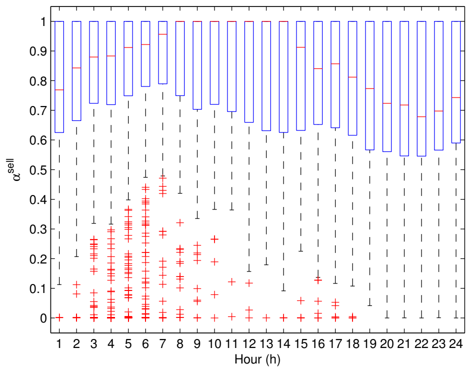


(2) Box plot of π^{sell} in each hour.

Figure B.1: Trends analysis for hourly imbalance prices.



(1) Box plot of α^{buy} in each hour.



(2) Box plot of α^{sell} in each hour.

Figure B.2: Trends analysis for hourly imbalance price ratios.

Taking into account these results, a probabilistic model for the imbalance prices is derived in this paper. As the actual daily market prices are known when bids to the intra-day market are prepared, instead of the prices themselves, the ratios α^{sell} and α^{buy} are used. The model estimates the value of α_t^{sell} and α_t^{buy} throughout the probability density functions built for each hour of the day from historical data of the previous two months. Then the imbalance prices forecasts, π_t^{sell} and π_t^{buy}, are obtained multiplying both ratios by the actual day-ahead market price in that period t.

This probabilistic model is integrated in the optimization process described below.

B.6 Optimal bidding strategy

The problem considered here is the optimization of the contracted energy by the wind producer in the intra-day market (IM), given a position in the daily market (DM) and taking into account the uncertainties of the involved random variables, to maximize the revenue on the electrical market.

Participation in the daily market consists in the sale of the power production forecasts available at the time of gate closure. A more complex strategy for this market has not been envisaged, since it has been estimated that the large uncertainties of the forecasts in the time range of that market would not yield better solutions, and would increase very much the computation time and the complexity of the problem.

The general expression for the revenues in a period t, R_t, obtained by a wind power producer which participates in the electricity market, can be expressed as:

$$R_t = g(P_{g,t}, \pi_{i,t}, \alpha_t; P_{i,t}) \tag{B.6}$$

where g is given by (B.1).

If $P_{g,t}$, $\pi_{i,t}$ and α_t are considered independent random variables, the probability density function f of the random variable R_t is

$$f(R_t) = f(P_{g,t}, \pi_{i,t}, \alpha_t) = f_{P_g}(P_{g,t}) f_{\pi_i}(\pi_{i,t}) f_\alpha(\alpha_t) \tag{B.7}$$

where $f_{P_g}(P_{g,t})$ and $f_{\pi_i}(\pi_{i,t})$ are the probability density functions of the random variables $P_{g,t}$ and $\pi_{i,t}$, respectively, and $f_\alpha(\alpha_t)$ may be expressed by

$$f_\alpha(\alpha_t) = \begin{cases} f_{\alpha^{sell}}(\alpha_t^{sell}), & P_{g,t} \geq P_{i,t} \\ f_{\alpha^{buy}}(\alpha_t^{buy}), & P_{g,t} < P_{i,t}. \end{cases} \tag{B.8}$$

Hence, the expected revenue for a period t will be a function of the power committed in the intra-day market at this period, and can be obtained by

$$\overline{R_t}(P_{i,t}) = E\left[R_t; P_{i,t}\right] = \iiint g(P_{g,t}, \pi_{i,t}, \alpha_t; P_{i,t}) f(P_{g,t}, \pi_{i,t}, \alpha_t)\, dP_{g,t}\, d\pi_{i,t}\, d\alpha_t. \tag{B.9}$$

Then, the optimization problem consists in finding the optimal position to be taken in the IM for the period t (taking into account the power committed in the daily market for that period), which maximizes the expected revenue for that period

$$P_{i,t_{opt}} = \arg\ max_{P_{i,t}} E\left[R_t; P_{i,t}\right] \tag{B.10}$$

subject to $0 \leq P_{i,t} \leq P_r$, $\forall t$, being P_r the rated power of the wind farm.

Although the IM price forecasting tool can compute the uncertainty of the forecasts, its consideration barely affects the results of the optimization process due to the high symmetry of the PDF of forecasts, and increases highly the computational cost. Consequently, deterministic forecasts for the IM prices are considered, and therefore, the objective function of the optimization problem can be simplified

$$\overline{R}_t(P_{i,t}) = E\left[R_t; P_{i,t}\right] = \iint g(P_{g,t}, \alpha_t; P_{i,t}) f(P_{g,t}, \alpha_t)\, dP_{g,t}\, d\alpha_t. \tag{B.11}$$

This problem may be discretized and solved easily by simple enumeration, and it must be solved for each time t, under the assumption of time-independent decisions over time. From historical data, possible values of $P_{i,t}$ are determined, $P_{i,t}^{min} \leq P_{i,t} \leq P_{i,t}^{max}$ and the range $P_{i,t}^{max} - P_{i,t}^{min}$ is split into a number of n_P classes or bins.

Omitting the subscript t, the expected revenue for a given quantity P_{in}, $n = 1, \ldots, n_P$ can be expressed as a discrete equation

$$\overline{R}(P_{in}) = \sum_{j=1}^{n_P} \sum_{k=1}^{n_\alpha} \left(g_{j,k}(P_{g_j}, \alpha_k; P_{in}) f_{j,k}(P_{g_j}, \alpha_k)\right) \tag{B.12}$$

where, n_P is the number of power bins, n_α is the number of imbalance price bins, P_{g_j} is the value of generated power, corresponding to the j-th power bin, and α_k stands for the k-th bin of the imbalance price ratio α (α^{buy} or α^{sell}, depending on the sign of the difference between P_{g_j} and P_{in}), for each period t. This equation is applied to the central value in every class.

The process followed in the optimal bidding strategy in each period t can be summarized in six steps:

Step 1. Forecast the IM price from historical DM and IM prices.

Step 2. Estimate buy and sell imbalance price ratios and their PDF from historical imbalance prices and actual day-ahead market prices.

Step 3. Compute the PDF for delivered and forecasted power from historical data.

Step 4. For each scenario of power delivered, power committed in the intra-day market and imbalance prices, compute the revenue and its probability taking into account the different PDFs (wind power forecasts and buy/sell imbalance prices forecasts).

Step 5. Compute the expected revenue for the representative value of each class, P_{in}, using (B.12).

Step 6. Select P_{iopt} as the value that gives the maximum revenue, as indicated in (B.10).

The process just described is very easy to implement, and historical data is updated for each period t considered.

B.7 Optimal risk-constrained bidding strategy

Due to the uncertain prices in the electricity markets, the optimal strategy just described could lead to some risky situations when extremely unforeseen imbalance prices occur. Then a risk management approach may result a good alternative to cope with these situations.

Optimization strategies tend to be risky, as they are based on the assessment of different prices (adjustment and imbalance). The predictability of imbalance prices is low, and this can lead to huge losses when buy imbalance prices take a very large value, which happens some hours per year. When generators become short, with a big difference between the bid offered to the market and the real production, high imbalance losses may be derived if this difference matches up with high buy imbalance prices. These losses can not be compensated by revenues in the opposite direction, because sell imbalance prices are bounded. Therefore, it seems reasonable to avoid the most risky situations, including a suitable measure of the risk aversion.

In the literature, several methods to define the attitude towards risk can be found in studies, such as Rockafellar & Uryasev [87], Weber [88], Morales et al. [15], Hussain et al. [89]. The most used are the inclusion of the VaR (Value at Risk) and CVaR (Conditional Value at Risk) parameters as a constraint in the optimization problem.

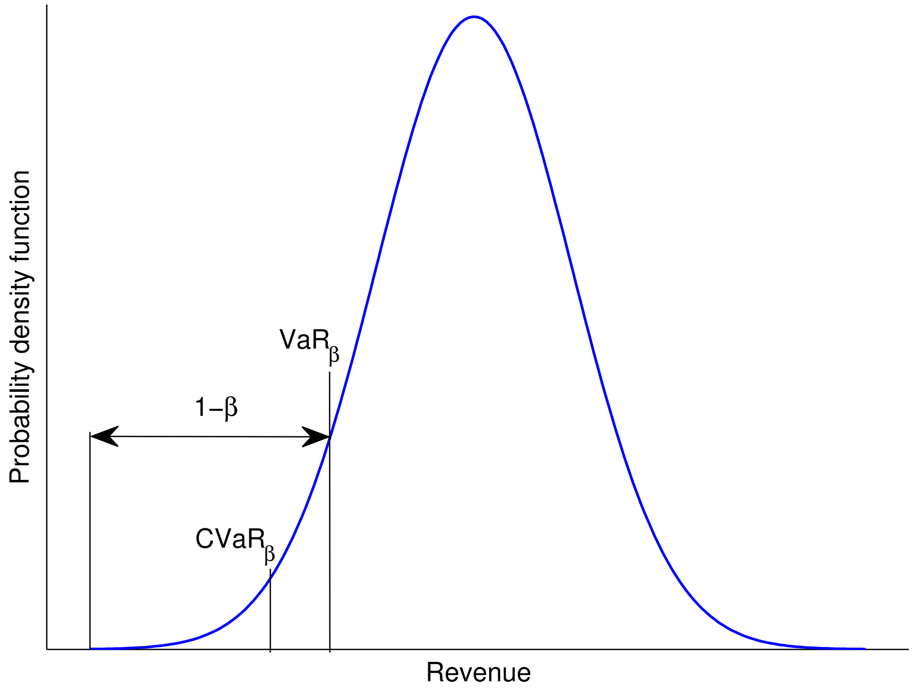


Figure B.3: VaR_β and $CVaR_\beta$ concept illustration.

Given a random revenue variable R, with cumulative distribution function $F_R(r) = P\{R \leq r\}$, the VaR of R with confidence level $\beta \in]0, 1[$ is

$$VaR_\beta(R) = max\{r \,|\, F_R(r) \leq 1 - \beta\}. \tag{B.13}$$

For random variables with continuous distribution functions, $CVaR_\beta(R)$ equals the conditional expectation of R subject to $R \leq VaR_\beta(R)$:

$$CVaR_\beta(R) = E[R \,|\, R \leq VaR_\beta(R)]. \tag{B.14}$$

The concept of VaR_β and $CVaR_\beta$ is illustrated in Figure B.3.

In this paper the CVaR parameter is employed, because, according to the literature (Jabr [83], Dicorato et al. [21], Dent et al. [24], Pousinho et al. [84]), it is very convenient for this purpose. The VaR possesses a discontinuous distribution as Rockafellar & Uryasev [90] points out, which can produce convergence failures in optimization problems. Furthermore, the VaR is not sensitive to extreme risky situations and only points out an upper risk limit, while the CVaR represents the tail mean and then provides an estimate of the weighted losses. Therefore, the CVaR is recommended for stochastic optimization.

The aim of the parameter is providing the maximum monetary risk expected by the participation of a wind power producer in the market for each period t. As this parameter assesses the risk of obtaining a level of incomes (or losses), previously defined in a given horizon with a confidence level β, a threshold ω for the revenues (or losses) which limits the risk, must be fixed.

The risk management restriction is integrated in the optimization strategy aiming to maximize the profit and reduce the risk, and the new optimization problem can be formulated for each period t, independently, as follows[3]:

$$\begin{aligned} P_{iopt} &= \arg\, max_{P_i} E[g(P_g, P_i, \alpha^{buy}, \alpha^{sell}; P_i)] \\ subject\ to & \\ & CVaR_\beta \geq \omega \\ & 0 \leq P_i \leq P_r, \end{aligned} \tag{B.15}$$

where

- $g(P_g, P_i, \alpha^{buy}, \alpha^{sell}; P_i)$ is the hourly revenue function of the wind power producer, given by (B.1) and (B.5);
- $CVaR_\beta$ is the CVaR risk measure of the revenue probability distribution g computed at the β confidence level for each class of P_i in each period t, i.e.,

$$CVaR_\beta = E[g(P_g, P_i, \alpha^b, \alpha^s) \,|\, g(P_g, P_i, \alpha^b, \alpha^s) \leq VaR_\beta(R)], \tag{B.16}$$

  with VaR defined by (B.13);
- ω is the incomes (losses) threshold to accept or discard the class of P_i tested in the period t;
- P_r the rated power of the wind farm.

The strategy is driven for each period t as follows:

Step 1. Forecast the IM price from historical DM and IM prices.

[3]For the sake of simplicity, the subscript t has been omitted.

Step 2. Estimate buy and sell imbalance price ratios and their PDF from historical imbalance prices and actual day-ahead market prices.

Step 3. Compute the PDF for delivered and forecasted power from historical data.

Step 4. For each scenario of power delivered, power committed in the intra-day market and imbalance prices, compute the revenue and its probability taking into account the different PDFs (wind power forecasts and buy/sell imbalance prices forecasts).

Step 5. From the revenue probability distribution obtained for each possible class of final power agreed in the intra-day market, P_{in}, compute the expected revenue and the VaR_β and $CVaR_\beta$.

Step 6. Select the class that maximizes the revenue in the period t considered, from those values of P_{in} that satisfy the restriction $CVaR_\beta \geq \omega$. If the restriction is never satisfied, then the last point forecast available at the time of updating the bids is used.

B.8 Case study

In order to assess the performance of the proposed strategies, a test-case has been prepared following the rules of the Spanish electricity market, as OMEL [33] establishes. The test-case consists in the participation of a wind power producer in the Spanish electricity adjustment markets during a period of 10 months in 2007, from March to December.

In this context, the wind power producer bids to the daily market the last prediction available at gate closure time, which takes place at 10:00 A.M., with a time horizons from 15 to 38 hours. After the DM gate closure, the position given for period t will be updated choosing the closest IM session to that period, and bids are thus presented with lead times varying from 3 to 7 hours. The time scheduling for bidding into the daily and intra-day markets is shown in Figure B.4, where the 'X' represent the moments when bids are presented and the numbers show the lead time for each period t.

The data of wind power come from the actual production of a 21 MW wind farm. Historic production and forecasts with time horizons up to 38 hours were used to compute the PDF of forecasts, as an approach to a probabilistic forecasting model for wind power production.

Actual prices in the Spanish electricity market (DM prices, IM prices and sell/buy imbalance prices) along the whole 2007 were collected but simulations were carried out for ten months (305 days) since data from the first two months were used as historical data to forecast IM prices and imbalance prices in March. In particular, deterministic forecasts for IM prices and a probabilistic estimate for the hourly imbalance prices (through a different PDF of the imbalance price ratios α^{sell}, α^{buy}) have been generated from the historical data.

The optimization strategies were programmed in Matlab®. Discretization was done considering 40 power bins ($n_P = 40$), 20 bins for the values of α^{sell} ($n_{\alpha^{sell}} = 20$) and a dynamic value for the number of bins for α^{buy}, ($n_{\alpha^{buy}}$), which depends on the maximum value of the historic α^{buy} values for each hour.

The bids presented to the daily market can be updated in the intra-day market following several strategies:

1. Use of point forecasts with sorter horizons (between 3 and 7 hours). This strategy is used as the reference for the comparison of results.

2. Calculate the optimal bid that maximizes the expected revenue for each hour, without risk management.

3. Calculate the optimal bid that maximizes the expected revenue for each hour, with a risk constraint limiting the minimum estimated revenue. A typical confidence level β of 0.95 has been used for this purpose and several values for the CVaR threshold, ω, have been tested, from -1000 € to 1000 € in steps of 100. For example, a value of $\omega = 0$ means that those power positions

		DAY D-1														
		10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
DAILY MARKET		X														
INTRADAY MARKET	S2													X		
	S3															
	S4															
	S5															
	S6															
	S1 (same day)															

		DAY D																							
		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
DAILY MARKET		15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38
INTRADAY MARKET	S2	3	4	5	6																				
	S3		X			3	4	5																	
	S4					X			3	4	5	6													
	S5									X			3	4	5	6									
	S6													X			3	4	5	6	7				
	S1 (same day)																		X			3	4	5	6

Figure B.4: Rules for updating bids in the intra-day market sessions (numbers inside the cells are the prediction horizons needed).

having an expected value below 0 €, for the 5% of the lowest revenues, will be rejected.

B.9 Results and Discussion

For each strategy and the whole period of time considered, 305 days in 2007, from March to December, the following results have been obtained:

- The total revenues R in M€.
- The total income in the intra-day market, R_{IM}, in €, related to the second term of the eq. (B.1).
- The total imbalance income, R_I, in €, corresponding to the term I_t in eq. (B.1).
- The average absolute power error $|\Delta P|$ in MW, calculated from the absolute power errors in each period t

$$|\Delta P|_t = |P_{i,t} - P_{g,t}| \tag{B.17}$$

where $P_{i,t}$ is the total power committed by the wind farm at hour t in the intra-day market and $P_{g,t}$ is the power actually delivered at that hour.

B.9.1 Optimal strategy

The results inferred from the optimal strategy without risk management compared with those from the point forecast strategy are summarized in Table B.2. It is shown that the optimal strategy increases in a 0.75% the total revenue for the wind power producer over a period of ten months, giving a profit of $10,400$ € ($1,040$ € per month in average).

As the total revenue increases, the average absolute power error increases in a higher percentage (72%), showing that the most profitable strategy for the wind power producer is not the one that minimizes the imbalances between the contracted and actual energy production. Also the imbalance income is more negative with the optimal strategy, which implies higher imbalance losses. The improvement in

	Optimal	Point forecast	Difference (%)
R (M€)	1.4028	1.3924	+0.75
R_{IM} (€)	$237,585$	$-30,384$	+882
R_I (€)	$-358,516$	$-100,871$	−255
$\lvert\Delta P\rvert$ (MW)	3.0677	1.7874	+72

Table B.2: Total revenues and power error for the optimal strategy vs. point forecast strategy.

the total revenue is due to the huge relative improvement of the income in the intra-day market (882%), i.e., the optimal strategy tends to bid more power than forecasted, selling more energy into the intra-day market.

Although the optimal strategy is profitable for the wind power producer, if the difference between hourly revenues obtained with both strategies is depicted, as in Figure B.5, it can be observed that there are some situations with important losses when bidding with the optimal strategy; losses at an hour may reach 900 € with optimal strategy whereas the maximum hourly losses are 150 € when bidding the point forecast.

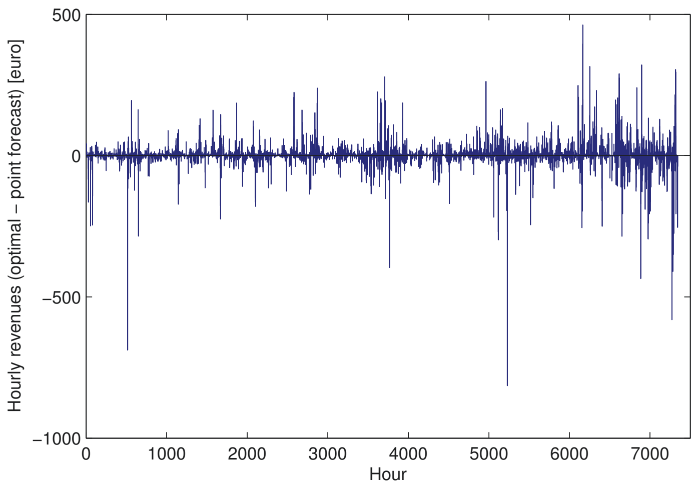


Figure B.5: Differences of hourly revenues (€) between optimal and point forecast strategies.

Trying to avoid these losses, a CVaR constraint has been included in the strategy, and results are presented below.

B.9.2 Optimal risk-constrained strategy

The optimization problem given by (B.15)-(B.16) is solved in this case.

The risk management was applied for several CVaR thresholds, from -1000 € to 1000 € in steps of 100 €. Controlling the threshold is a way of controlling the risk aversion, as risk aversion increases with higher values of the threshold.

The revenues obtained with the different thresholds in the risk-constrained strategy are depicted in Figure B.6. Also the total revenue obtained with both non-risk-constrained strategies (optimal and point forecast) are included in the same figure for an easier comparison of results. It can be observed, on the one hand, that the more severe the restriction (i.e., greater CVaR threshold) the more similar is the result to that obtained with point forecasts. On the other hand, if risk aversion is low (lower CVaR threshold), revenues tend to the value obtained with the optimal strategy.

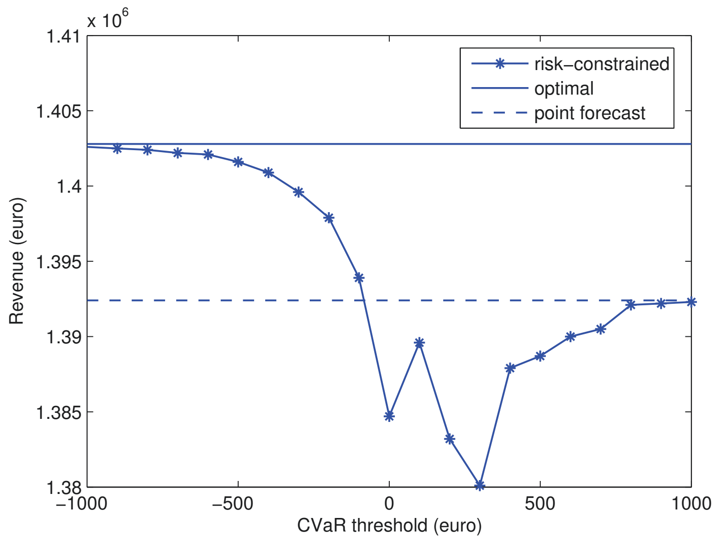
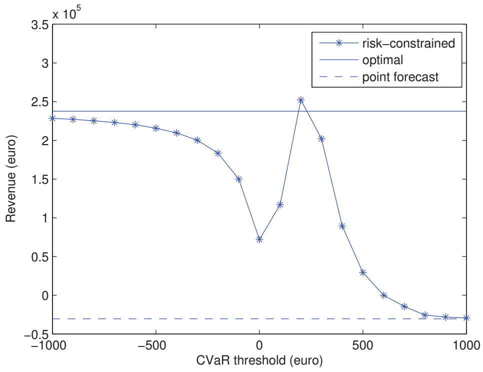
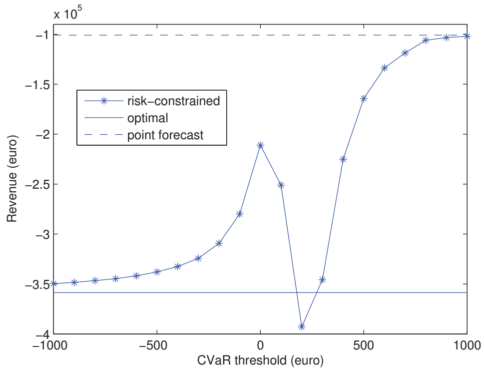


Figure B.6: Revenues obtained with the different strategies.

Then, it can be said that the risk-constrained strategy does not improve the revenue obtained by the wind power producer with the optimal strategy. Moreover, for thresholds ranging from 0 € to 1000 €, results are worst than for the point



(1) Intra-day market revenue.



(2) Imbalance term revenue.

Figure B.7: Intra-day market revenue and imbalance term revenue obtained with the different strategies.

forecast strategy. In order to explain this behavior, the total income in the intra-day market and the total imbalance income have been represented in Figure B.7. In general, it can be said that the more risk aversion (i.e., the greater CVaR threshold) the fewer losses due to imbalance (Figure B.7b), but also the fewer revenues in the intra-day market (Figure B.7a). For a threshold of 200 €, the higher revenue in the intra-day market is obtained, but also the higher imbalance loss, and then, the total revenue is the lowest.

From Figure B.7a, it may be deduced that the more severe the CVaR constraint, the less power is sold in the intra-day market. Note that the revenue in that market is negative when the CVaR threshold is greater than 600 €, i.e., the wind power producer is buying energy in those cases.

Regarding the power errors, the average absolute power errors obtained with the different strategies are depicted in Figure B.8. When the revenue is limited by the values obtained with the non-risk-constrained strategies (this happens for negative CVaR thresholds, as seen in Figure B.6), the average power error is always greater than the power error of the optimal strategy, and therefore, the risk-constrained strategy does not benefit to the power system either.

Contrary to expectations, the higher losses of the optimal strategy were not avoided in any case. These losses were due to unforeseen imbalance prices, so it is suggested that another model for estimating imbalance prices would be suitable when managing the risk.

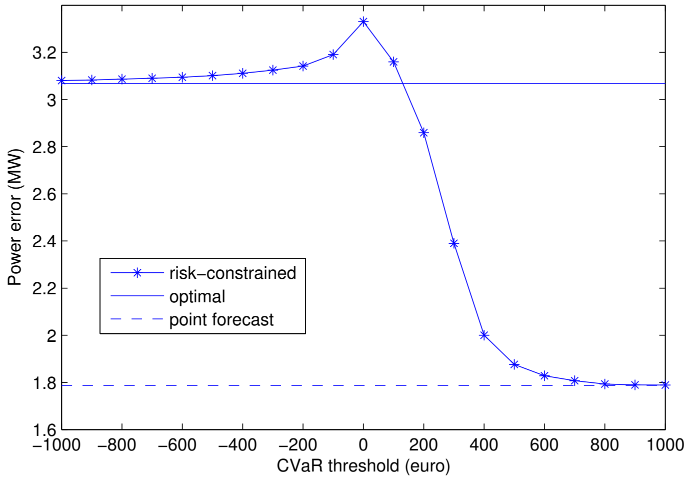


Figure B.8: Average absolute power error obtained with the different strategies.

B.10 Conclusions

From the simulations run, and under the assumed hypothesis, the following conclusions may be drawn:

- Strategic bidding in the intra-day market can be used to improve even more the revenues of the wind power producer. The optimal strategy described in this paper includes deterministic intra-day price forecasting as well as probabilistic power forecasting and probabilistic imbalance prices forecasting from historical data. The strategy tends to sell more energy in the intra-day market than forecasted, improving the incomes in that market although the imbalances between contracted and actual production increase. Power imbalance decrease is not encouraged, suggesting an inadequate regulation of the imbalance prices in the case of the Spanish Market.

- When applying a risk management strategy, the less severe the restriction is, the higher incomes are obtained, but an upper limit for the revenue can be established, which tallies with the optimal strategy revenue. Again, it is shown that a decrease in the imbalance costs does not imply an increase in the revenues. The risk-constrained strategy seems to benefit neither the wind power producer, nor the electric power system, because the higher losses of the optimal strategy are not avoided and power errors are greater.

As the higher losses have been due to extreme unforeseen imbalance prices, further research in the modeling of their uncertainty could lead to higher benefits of the prepared risk-constrained strategy.

Acknowledgments

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Appendix C

Analysis of the imbalance price scheme in the Spanish electricity market: a wind power test case

C.1 Abstract

This work investigates the interaction between wind power and electricity markets. The paper is focused on balancing markets pricing policies. The proposal of a new imbalance price scheme is included and conveniently evaluated. This proposed scheme tries to minimise the use of ancillary services to compensate for deviations in searching for a more efficient market design. The effectiveness of imbalance prices as market signals is also examined, and policy recommendations regarding imbalance services are discussed. Two tests cases are included that analyse the participation of a wind power producer in the Spanish electricity market using a stochastic optimisation strategy. For this purpose, the uncertainty of the variables is considered, i.e., wind power production and prediction, intraday and imbalance prices. Test cases were run with real data for 10 months, and realistic results are presented along with a hypothetical test case. The regulation of the imbalance prices may not be adequate for the Spanish electricity market because an error drop is not sufficiently encouraged. Therefore, we suggest the application of a new imbalance price scheme, which includes an additional constraint. The conclusions of this article can be assumed to be general policy recommendations.

C.2 Introduction

Because electricity markets liberalisation, intermittent energies should participate in such a scheme. This interaction is two-fold; on the one hand, renewable energy sources for electricity (RES-E) assume risks that originate from market participation, and consequently, RES-E should pay the costs of the deviations produced in the power system. On the other hand, regulations should enhance RES-E participation, as they possess positive environmental externalities.

Regarding the first issue, in the Spanish electricity market case, wind power producers participate in a similar manner as conventional plants, except that they receive a feed-in tariff to compensate for market risks. For this, the producers should forecast their expected production to bid it to the market during the settlement period. Generally, their production is estimated using short-term wind power production tools, which usually provide the forecasted power level and the associated uncertainty. The accuracy of these tools has been widely studied in the literature, including in studies by González et al. [6], Martí et al. [7], Pinson et al. [8]. Today, great development in this field provides us with very precise predictions. However, the deviations between forecasted and committed power produce imbalances, which should be paid by the wind power producers, as suggested by Fabbri et al. [9], Holttinen [10], Bathurst et al. [11]. Therefore, some scientific works have focused on considering the uncertainty of the prediction to reduce the imbalance costs. Given that an estimation of the uncertainty should be provided, several approaches to determine this uncertainty can be considered, including those described by Pinson et al. [12], Monteiro et al. [13], Nielsen et al. [14], Pinson et al. [8], Morales et al. [15]. Once the uncertainty has been estimated, several techniques can be used to reduce the effects of deviations from initial schedules. Optimisation strategies can be widely employed to reduce economic losses and, consequently, improve the revenues. Accordingly, these strategies are based on updating the bid made to the daily market in the intraday market, when predictions with shorter horizons are available; the accuracy of the predictions thus rises. These methods can be found in studies by Fabbri et al. [9], Holttinen [10], Angarita-Márquez et al. [16], Usaola & Angarita [17], Usaola & Moreno [18], Bourry & Kariniotakis [19].

However, market participation risks do not only rely on power deviations, as electricity market prices are highly variable and difficult to forecast. Therefore, an estimation of these prices is a relevant problem. Due to the unavoidable difference between the produced and committed power, the imbalance costs borne by wind power producers are especially important, and the imbalance prices should thus be considered. While most studies are not based on actual balancing energy prices and only consider estimations (Holttinen [10], Fabbri et al. [9], Matevosyan & Soder [20], Angarita-Márquez et al. [16]), realistic assumptions can be found in certain studies, such as Bueno et al. [1], Moreno et al. [2].

In addition to the optimisation strategy, risk management restriction can be considered in an effort to reduce the hazard of having extremely high imbalance losses or to reduce the deviations produced in the power system. These methods consider the variability of imbalance prices and/or production and address them to reduce the risk of incurring excessive costs. These methods can be found in previous studies by Dicorato et al. [21], Botterud et al. [22], Bourry et al. [23], Moreno et al. [2], Dent et al. [24].

In the literature, some works analyse the market design. Most researchers focus on support schemes, such as Rivier-Abbad [25], Klessmann et al. [26], Hiroux & Saguan [27], but the studies also include other integration issues, including technical and economic issues. Other articles analyse the design and structure of the balancing prices scheme, such as those by Barth et al. [28], Vandezande et al. [29], Weber [30]. Thus, in these works, a trade-off between the effect of market signals on the behaviour of wind generators and efficient support schemes is suggested, and some policy recommendations are included. Although these works analyse the present regulation, none of them are based on particular test cases.

This paper addresses the interaction between the electricity market and wind energy. An optimal participation of wind power producers in adjustment markets, which is focused on reducing imbalances, is investigated. The optimisation process is stochastic and considers the uncertainty of both market and production variables, i.e., short-term wind power prediction, intraday prices and imbalance prices. This study is conducted in a realistic manner, as actual market prices and wind power productions are employed to assess the results. Moreover, data for one year were collected; therefore, a thorough analysis was performed. These test cases were run, and their results are conveniently discussed and related to a regulation analysis. Furthermore, policy recommendations that are applicable to the imbalance price scheme are suggested and tested.

Below, the main contributions of this work are explained. First, the inclusion of a risk management analyses entails deviation reductions. This test is performed using real data; thus, realistic scenarios are considered. The analysis performed is exhaustive, as a large quantity of data is considered through a stochastic optimisation that addresses the uncertainties associated with the variables. Second, diverse test cases are used to analyse the effectiveness of Imbalance Prices (IP) as market signals. For this, the imbalance pricing and the diverse power producers' behaviours under the present regulations are analysed to develop a new cost-reflective imbalance price scheme, which is also proposed and tested. Finally, policy recommendations are designed to prevent an overuse of balancing services. In this test case, the production and forecasts of a wind farm of 20-MW rated power is employed along with the historical data of market prices, that is, daily, intraday and imbalance prices. The optimisation strategy was programmed in Matlab and, because of its simplicity, can be easily integrated in a real-time routine.

The aim of this work is two-fold; on the one hand, it assesses the sensitivity of producers to market signals. On the other hand, the efficiency of the imbalance prices scheme is evaluated. Given the assumption that the regulation of imbalance market prices should foster the reduction of power system balancing costs and, thus, promote the diminution of unexpected deviations, a new imbalance price scheme is proposed.

The paper begins with a description of the Spanish electricity market structure, which includes daily, intraday and imbalance markets. Later, a short introduction to wind power participation in electricity markets is provided. This section includes a discussion on short-term wind power forecast and the prediction and modelling of market prices in the intraday market and balancing services. Next, the formulation of the optimisation strategy for bidding in intraday markets is discussed. Then, an analysis of the current imbalance prices scheme is performed, and a new proposal is included. Finally, the participation of a wind farm in the Spanish electricity market is simulated over nearly a year under diverse assumptions. First, results following an optimal strategy are presented with the present imbalance price scheme, and the proposed imbalance prices scheme is then tested for diverse risk attitudes. The results are compared with reference cases based on point predictions. Section C.8 summarises the conclusions of this study.

C.3 Spanish electricity market

The electricity market is composed of a set of sub-markets in which generators participate to sell their hourly power production. Generally, producers participate in the daily market (DM). Afterwards, they may update their productions in the adjustment or intraday markets (IMs). Finally, the transmission system operator (TSO) addresses real-time deviations through ancillary services and, if necessary, draws on the imbalance management process. These markets processes are explained in the following sections.

C.3.1 Daily market

In the DM, bids must be made between 14 and 38 hours before the operation settlement period (OSP). In the Spanish case, the gate closure time is 10 a.m. This market possesses the largest liquidity, as most energy is negotiated on it.

C.3.2 Intraday markets

These markets may be continuous or composed of several sessions, as in the Spanish case, where 6 intraday market sessions are held. The Spanish IM sessions occur 4 to 7 hours before the OSP. The structure of this market is described in Table C.1, where it can be appreciated that IM sessions overlap in different OSPs.

Session number	1	2	3	4	5	6
Session Opening	16:00	21:00	01:00	04:00	08:00	12:00
Session Closing	17:45	21:45	01:45	04:45	08:45	12:45
Schedule Horizon	28h	24h	20h	17h	13h	9h
Hourly Periods	21-24	1-24	5-24	8-24	12-24	16-24

Table C.1: Spanish intraday markets structure

In these markets, producers may sell and purchase energy to reduce for the deviations between the scheduled power production in the DM and the available forecasts at the IM session time.

C.3.3 Imbalance markets

During the interval between the last gate closure of an intraday market session and opening of the next one, deviations between scheduled and measured energy are addressed through ancillary services based on market procedures, such as secondary reserve, tertiary reserve and imbalances management process.

Secondary reserve

The secondary reserve is an optional ancillary service. The aim of this procedure is two-fold: to compensate for the power deviations and to maintain the power system frequency reference value. This ancillary service is provided by regulation zones, composed of several generators gathered in a zone and named energy scheduling units, which have the responsibility of fulfilling the requirements of the TSO. This service is paid for by two concepts using market procedures: availability (secondary reserve) and utilisation (energy). In the market process, generators bid both up and down secondary reserve power and their respective prices. These bids are allocated using minimum costs procedures, considering system constraints, to obtain a marginal up/down secondary reserve price.

Tertiary reserve

This ancillary service is managed according to market procedures. Although it is mandatory, only previously authorised generators can participate in the tertiary reserve markets. This service is aimed to restore the secondary reserve band. The marginal up/down prices of the entire tertiary reserve market is obtained from the allocation of both up and down bids and their respective prices, using minimum costs procedures. Moreover, power systems constraints could modify the initial market schedule.

Imbalances management process

The imbalances management process is an optional service aimed to solve the differences between power generation and demand that can occur from the gate closure of one intraday market session until the first period of the horizon of the next intraday market session. Conventional power producers, pump storage and manageable renewable energies can participate in these markets. The TSO can call for bids depending on the amount of forecasted deviations between generation and demand. In the process, the energy scheduling units that are able to participate in the imbalance market bid their increasing and decreasing energy programme. Once the bids have been allocated, the price for all scheduled modifications is the marginal price of the short/long imbalances.

C.4 Wind power in electricity markets

Generally, wind power producers bid the last power predictions in the daily market and update the predictions in the intraday markets, when shorter forecast horizons are available and, thus, predictions are more accurate. As there is an unavoidable deviation between the power committed and finally produced, wind power producers frequently incur imbalances. These deviations should be paid at imbalance prices, as these costs suppose a burden to wind power producers and have negative effects, thus reducing the incomes obtained during the market participation.

As the IMs have less liquidity than the DMs, some problems may arise with the participation of significant wind power in the IM (very likely buying or selling energy simultaneously). The effect of increased wind power in the IM must still be evaluated and is not considered in this work.

C.4.1 Revenues of a market participant

The general mathematical expression of the revenue R_t obtained by a wind farm participating in the electricity market in a period t may be generalised as

$$R_t = DM_{inc,t} + IM_{inc,t} + IT_t = P_{d,t}\pi_{d,t} + \pi_{i,t}(P_{i,t} - P_{d,t}) + IT_t \tag{C.1}$$

where DM_{inc} and IM_{inc} are the incomes obtained in the daily and intraday markets, respectively, and IT corresponds to the imbalance term (costs/ incomes). Then, the right-side formula expresses the revenues as a function of market prices and powers for a settlement period t, where $P_{d,t}$ and $P_{i,t}$ are the estimations of the future produced power in the DM and IM for the wind farm, respectively. The forecast of power production is updated at the intraday market time, and the power committed in IM is thus $P_{i,t} - P_{d,t}$, as the power previously traded in DM is $P_{d,t}$ for a given hour t. Furthermore, $\pi_{d,t}$ and $\pi_{i,t}$ are the marginal prices of energy in the DM and IM, and IT_t is the imbalance term for that period t, whose expression is

$$IT_t = \begin{cases} \pi_t^{sell}(P_{g,t} - P_{i,t}) & P_{g,t} > P_{i,t} \\ \pi_t^{buy}(P_{g,t} - P_{i,t}) & P_{g,t} < P_{i,t} \end{cases} \tag{C.2}$$

with $P_{g,t}$ being the power actually generated by the wind farm in the period t and π_t^{sell} and π_t^{buy} being the imbalance prices for overproduction (positive imbalance) and underproduction (negative imbalance), respectively.

Typically, $\pi_t^{sell} \leq \pi_{d,t} \leq \pi_t^{buy}$, and they may be written as

$$\begin{aligned} \pi_t^{sell} &= \alpha_t^{sell}\pi_{d,t} \\ \pi_t^{buy} &= \alpha_t^{buy}\pi_{d,t} \end{aligned} \tag{C.3}$$

with $\alpha_t^{sell} \leq 1$ and $\alpha_t^{buy} \geq 1$.

In the next sections, the variables involved in the problem are described.

C.4.2 Short-term wind power prediction uncertainty

Today, weather prediction programmes or real-time SCADA data provide estimations of the expectation of the future power production of a wind farm. These tools are commonly called short-term wind power prediction programmes and supply the forecast of the average hourly power for the upcoming hours. These predictions have diverse accuracies, which are determined as the time horizon decreases, as presented by Martí et al. [7].

Forecasting tools can provide deterministic predictions, also called *point predictions*, as well as the uncertainty associated with the prediction. This additional information can be considered when power producers bid to market. Obtaining an estimate of this uncertainty is beyond the scope of this paper. Instead, estimates originating from past data are used likewise in Usaola & Angarita [17]. In this paper, past predictions and productions of a wind farm were tabulated to obtain their frequency distribution, composed of predictions and their uncertainties, which were employed as an approximation of their probability distribution function (PDF), and included in the optimisation strategy.

C.4.3 Uncertainty of market prices

The participation of wind energy producers in electricity markets may imply a prediction of future market prices to enhance the revenues obtained by wind power producers and to improve market integration. It is important to correctly estimate the future market prices to adopt a sensitive behaviour to market signals, thus reducing the probability of incurring expenses.

Moreover, market price forecasting is a challenge for wind power integration because the characteristics of electricity markets result in the intricate behaviour of market prices. As demonstrated by Nogales et al. [86], electricity prices possess a complex dynamic structure because electricity is non-storable and due to the insufficient liquidity of electricity markets. Thus, a meticulous analysis of market prices structure must be performed to extract the necessary information to construct suitable models.

Intraday market price forecasting tool

Disposed with an accurate forecast of intraday market prices, it is necessary to improve the market bidding strategies for both producers and consumers. A correct estimate of these prices may be used to reduce imbalance costs.

In this work, the IM price prediction uses a time series model, where the structure of the Spanish electricity market is assumed. The model of the prediction tool is explained in depth in Bueno et al. [1].

Imbalance price analysis

In the Spanish electricity market, the imbalance prices are highly variable and difficult to forecast. Due to the unavoidable imbalance between scheduled and generated energy, these imbalance prices are very important for a wind power producer. In fact, in the Spanish power system, wind generators are the source of much of the entire system imbalance, as indicated by Red Eléctrica de España [32].

Imbalance prices also have high volatility because the number of participants and the amount of energy exchanged are relatively low and (in dual pricing systems) because of the random nature of the overall imbalances.

In this paper, the heuristic approach presented by Bueno et al. [1] is followed when imbalances prices are modelled. In the aforementioned study, the values of the hourly prices in 2007 were collected and employed to forecast the imbalance prices, using their historical values to estimate the future prices. For this purpose, imbalance prices of the previous two months were collected to obtain an approximation of their PDFs, constructing a separate model for every hour. This assumption is valid for both the sell and buy prices. As actual daily market prices are known when the bid is calculated, instead of the prices themselves, the parameters α_t^{sell} and α_t^{buy}, described in eq. (C.3), were used to employ the DM prices to estimate the imbalance costs/revenues. Subsequently, these estimates are integrated in the optimisation bidding strategy, which is described below.

C.5 Optimal bidding strategy

When a wind power producer participates in electricity markets, it is possible to follow an optimisation strategy to increase the revenues obtained. These strategies are commonly based on electricity price forecasts, assessing the incomes of participating in several markets under probabilistic assumptions. In this section, the bidding strategy used by wind power producers is mathematically formulated. The subscript t was eliminated because of simplicity in the next expressions. First, the general expression for the revenue equation, R, of a wind power producer, which participates in the electricity market, can be expressed as

$$R = g(P_g, \pi_i, \alpha; P_i) \tag{C.4}$$

where α represents imbalance prices ratios, defined by eq. (C.3). Because g is given by eq. (C.1), and P_g, π_i, α are considered independent random variables, following the same assumptions made in Bueno et al. [1], the optimisation problem can be posed as

$$\begin{aligned} P_{i,opt} = \arg\max_{P_i} E\left[R; P_i\right] \\ 0 \leq P_i \leq P_r \end{aligned} \tag{C.5}$$

where $E\left[R; P_i\right]$ is the expected revenue, with $P_{i,opt}$ being the optimal position to be taken in the IM, which accounts for the bid made in the daily market, and P_r is the rated power of the wind farm. The prediction tool described in Bueno et al. [1] is employed to provide the future prices of the intraday market. A deterministic estimate of IM prices is employed in the optimal bidding strategy. This tool can provide the uncertainties of the intraday market prices; however, these values are not included in the optimisation process because of the high computational cost and the limited improvements of its use. Due to the high symmetry of the PDF of the forecasted intraday market prices, the incorporation of these parameters negligibly affects the results of the optimisation process.

Consequently, the objective function of the optimisation problem can be simplified as

$$\overline{R} = E\left[R; P_i\right] = \iint_{-\infty}^{\infty} g(P_g, \alpha; P_i) f(P_g, \alpha)\, dP_g\, d\alpha \tag{C.6}$$

This problem may be discretised and solved easily using simple enumeration, and it must be solved for every hour t. Then, the expected revenue for a given power bid in the IM can be expressed as a discrete equation, such as

$$\overline{R} = \sum_{j=1}^{n_P} \sum_{k=1}^{n_\alpha} (g_{j,k}(P_{g_j}, \alpha_k; P_i) f_{j,k}(P_{g_j}, \alpha_k)) \tag{C.7}$$

where

- n_P: number of power bins.
- n_α: number of imbalance price bins.
- P_{g_j}: bin value of generated power, corresponding to the $j-th$ power bin.
- α_k: bin value of imbalance price, corresponding to the $k-th$ alpha bin.

To determine the value of the power bid in the IM, the range of power is divided into intervals (n_P=20), and the average worth of any interval is assigned to P_i. Analogous methods are applied to obtain bin values of generated power and imbalance prices. In the latter, the number of bins is different for each hour of the day, as the PDF is dynamically obtained as a function of historical data.

C.5.1 Risk assessment strategies

Due to the electricity market prices uncertainty, complementing the bidding strategy with a risk management approach may be pursued.

Then, if some risk parameters are selected, the minimum expected incomes will be foreseeable, and it will thus be possible to assess the risk before the bid to market. Generally, incomes are related to the probability of occurrence because of the uncertainties of the variables involved in the problem. Because the revenue values and their probabilities can be estimated a priori using historical data, a PDF can be built to assess the risk. Once the PDF has been obtained, the risk prone/averse of decision makers should be defined. Consequently, it must be a goal to define the minimum revenues limit; for this purpose, a restriction is included in the optimal bidding strategy.

Risk constraints aim to avoid the most risky strategies, including the uncertainty of the random variables. This principle means that a suitable measure of this risk should be used to improve the economic results and to produce lower errors in the power system. For this purpose, a risk-constrained parameter may be included in the optimal strategy, to reduce the tendency of the risk, and model a risk-neutral behaviour.

The most frequently used parameters to limit risk behaviour are VaR (Value at Risk) and CVaR (Conditional Value at Risk). The first is a measure defined as the minimum profit value such that the probability of the profit is lower than or equal to $1-\beta$, i.e., $VaR_\beta(I) = min[z|F_I(z) \leq 1-\beta]$. The latter is the expectation of the tail VaR, i.e., the lowest profit outcomes distribution mean not exceeding VaR.

Mathematically, given a random incomes variable I, whose cumulated PDF is defined by $F_I\ (z)$, with z being a random variable associated with incomes given a probability, the CVaR is defined as follows:

$$CVaR_\beta(I) = \int_{-\infty}^{\infty} z \mathrm{d}F_I^\beta(z) \tag{C.8}$$

$$F_I^\beta(z) = \begin{cases} 0, & \text{where } z < VaR_\beta(I) \\ \frac{F_I(z)-\beta}{1-\beta}, & \text{where } z \geq VaR_\beta(I) \end{cases}$$

where β is the confidence interval of the revenues distribution function. In this paper, the parameter CVaR is selected as a measure of the risk. CVaR is strongly recommended in the literature because of its mathematical behaviour, better convergence properties, and its increased sensitivity to extremely risky situations, as it provides a measure of the average tail losses and not only a lower limit. Weber [88] and Rockafellar & Uryasev [87] recommend this parameter for stochastic optimisation.

The aim of the parameter is to provide a minimum incomes expected threshold, which guarantees obtaining a profit. Consequently, the optimisation problem can be formulated as follows:

$$\begin{array}{lll} P_{i,opt} = & \arg\max_{P_i} & E[g(P_g, P_i, \alpha^b, \alpha^s; P_i)] \\ & s.t. & CVaR_{\beta(I)} \geq \omega \end{array} \tag{C.9}$$

where,

- $g(P_g, P_i, \alpha^b, \alpha^s; P_i)$ is the revenues function of the wind power producer.
- $CVaR$ is the parameter employed in the risk management strategy. It measures minimum revenues.
- β is the confidence level for CVaR.
- ω is the threshold of CVaR, i.e., the minimum required value for the incomes.

C.6 Imbalance prices policy

In this section, the mechanism employed to set the value of imbalance prices is explained. These prices are applied to those producers that deviate from the schedule after intraday markets. These prices penalise generators who incurred imbalances using the value of these deviations for the system. Moreover, a new regulation proposal is included and discussed.

An overview of existing imbalance price mechanism was presented by ETSO [71], in which two types of imbalance price mechanisms are described:

- Dual imbalance pricing, where a different price is applied to positive imbalance volumes and negative imbalance volumes; or
- Single imbalance pricing, where a single imbalance price is used for all imbalance volumes.

In cases where a dual imbalance pricing regime is followed, the main price is applied to imbalance volumes in the same direction as the overall market, whereas the reverse price is applied to imbalance volumes opposite in direction to the overall market, e.g., "short" when the market is "long", or vice versa.

A discussion about the advantages and disadvantages of using each mechanism can be found in studies by Weber [30], Vandezande et al. [29], Barth et al. [28]. In these papers, a single price system is recommended because of the negative effects of dual imbalance pricing in both the liquidity of IM and the penalisation of wind power producers.

C.6.1 Present imbalance prices scheme

For the Spanish electricity market, a two price system scheme is used, and different prices are fixed for over-deviations (Sell Price) and under-deviations (Buy Price).

To determine the Sell Price (SP) and Buy Price (BP), the TSO calculates the hourly net balance of up and down energies (NBUD) allocated in the tertiary reserve, secondary reserve markets and the deviation management procedure, if any. This balance determines how the prices will be set depending on whether volumes of imbalances are in the same direction as the overall market. Then, the TSO computes the cost for the system of paying the secondary reserve, tertiary reserve and imbalance management process energies to determine the weighted average price of the overall up and down energies, obtaining the following:

- WAPD: weighted average price of management imbalances, tertiary and secondary reserve for down energies. It may be applied to pay positive deviations (Sell Price) because it is the cost of reducing the supplied energy to balance long deviations.

- WAPU: weighted average price of management imbalances, tertiary and secondary reserve for up energies. It may be applied to negative deviations (Buy Price), as it is the cost of increasing the committed energy to compensate for short deviations.

If this value WAPD/WAPU does not exist, i.e., NBUD is negative for the BP case or positive for the SP case, the imbalance price worth is set to the marginal DM price. In short, the mechanism to set imbalance prices is presented in Table C.2, where MDP signifies the marginal daily price, and the system requirements are determined by the positive or negative value of NBUD.

		Net Balance Energy(NBUD)	
		Positive	Negative
GENERATOR PRODUCTION	LONG	MDP	min(WAPD,MDP)
	SHORT	max(MDP,WAPU)	MDP

Table C.2: Dual imbalance price system scheme in the Spanish electricity market

Then, the imbalance price scheme reflects, at least, the cost of imbalances to the power system, as it is a measure of how much is paid to compensate for the deviations originating from the secondary reserve, tertiary reserve and imbalance management processes.

C.6.2 Imbalance price regulation proposal

Although imbalance prices consider the expenses of deviations for the power system, they should also aim to reduce these imbalances, as they imply the use of ancillary services, which should be avoided or reduced. For occasions when imbalance costs (short or long deviations) are higher than intraday market expenses (π_i), wind power producers may find more profitable to pay (or buy) imbalances than to update their forecast errors in intraday markets. This behaviour has a negative effect in the power system, as following an optimisation strategy based on price predictions may result in imbalances because it is more lucrative. In this sense, this possibility should be restricted.

First, the latter statement is mathematically demonstrated. For this, it is assumed that wind power producers have participated in DM and an attempt to reduce imbalances by updating their bids in IM will be made. As previously explained in eq. (C.1), incomes resulting from intraday market participation (IM_{inc}) are defined by

$$IM_{inc} = \pi_i(P_i - P_d)$$

Similarly, the imbalances worth, can be determined by eq. (C.2). Thus, the total revenues obtained by updating the DM bid will be

$$UT = \begin{cases} -\pi_i P_d + \pi_i P_i + \pi^{sell}(P_g - P_i) & P_g > P_i \\ -\pi_i P_d + \pi_i P_i + \pi^{buy}(P_g - P_i) & P_g < P_i \end{cases} \tag{C.10}$$

where UT means update term and accounts for the participation of wind power producers in IM, including the imbalance term. The term $-\pi_i P_d$ is a fixed cost for wind power producers because it depends on the power bid to the daily market and the IM price, and it is considered a previously made decision that cannot be modified in this step.

For short deviations, that is, $P_g < P_i$, the update term (UT_s) is

$$UT_s = -\pi_i P_d + (\pi_i - \pi^{buy})P_i + \pi^{buy} P_g$$

In cases where $\pi^{buy} < \pi_i$, there is an incentive to declare the maximum power in the IM.

To quantify the importance of this fact, in 2007, for 24.52% of the hours, the buy imbalance price was higher than the intraday price; thus, this case occurs frequently in the Spanish electricity market.

In contrast, when long deviations occur, i.e., $P_g > P_i$, the UT_l is

$$UT_l = -\pi_i P_d + (\pi_i - \pi^{sell})P_i + \pi^{sell} P_g$$

Thus, in those cases where $\pi^{sell} > \pi_i$, reducing the power bid in the IM will be more profitable than being paid at the imbalance sell price. In other words, selling in imbalance markets produces a bigger return than updating the production in IM.

The frequency of occurrence of this case was quantified in 2007, where the sell price was observed to be higher than the intraday price in 18.8% of cases.

Because of this evidence, a new regulation may be included in the imbalance price scheme. This regulation includes a new constraint, i.e., that the BP (Buy Price) must be higher or equal than both the intraday prices (π_i^n) and the marginal daily prices (π_d) and not exclusively indexed to the latter. For the Sell Price (SP), analogous reasoning is applied, and the SP must be lower than or equal to both the intraday prices and marginal daily prices. Therefore, the new Reference Buy Price (RBP) and Reference Sell Price (RSP) could be defined as

$$RBP = max(\pi_d, \pi_i^1, ..., \pi_i^6)$$

$$RSP = min(\pi_d, \pi_i^1, ..., \pi_i^6)$$

Then, these reference prices, RBP and RSP, are suggested to be included in the imbalance prices scheme such that imbalance prices will be indexed to these values. The new regulation proposal is summarised in Table C.3.

		Net Balance Energy(NBUD)	
		Positive	Negative
GENERATOR PRODUCTION	LONG	RSP	min(WAPD,RSP)
	SHORT	max(RBP,WAPU)	RBP

Table C.3: Proposed imbalance pricing scheme for the Spanish electricity market

Therefore, although the cost of ancillary services is included in the current imbalance prices scheme, IP cannot be used as adequate market signals, as they do not foster the reduction of imbalances, and an overuse of ancillary services is thus possible. Because imbalance costs are not transferred to producers on every occasion, producers are not able to have a good sensitivity concerning the effects of their deviations in power systems. This new imbalance price scheme aims to foster that when wind power producers update their forecast in IM, they should be economically motivated to reduce the errors of power production. On the other hand, if wind power producers errors are not reasonably reduced, and instead of that, they buy imbalances, the wind power producers should be penalised. Then, the risk of balancing services overuse should be limited. In conclusion, a proposal that indexes buy/sell prices to the maximum/minimum value of both the intraday price and daily price will foster the effectiveness of imbalance prices as market signals.

C.7 Results

Based on the mathematical formulation described in the previous sections, several simulations were performed to study the effects of applying the new regulation imbalance pricing scheme and determine how wind power producers may bid following an optimisation strategy based on price forecasts. In this section, the results of two cases, under different balancing prices schemes, are provided and compared with reference cases.

The tests were performed in a realistic manner. For this purpose, real power and price values were selected to evaluate the efficiency of bidding strategies.

In the proposed imbalance pricing scheme, prices corresponding to a new regulation were simulated and employed. For this, new imbalance prices were created by applying restrictions, described in Table C.3, to actual prices from 2007. Because wind power producers only update their bids once for a certain hour t, such that they bid when shorter horizons occur, a simplification was performed to calculate reference sell and buy prices. Therefore, only one intraday price was considered to calculate reference prices, taken as the price of the intraday session with shorter horizons; thus, the reference prices were computed as follows:

$$RBP = max(\pi_d, \pi_i^n)$$

$$RSP = min(\pi_d, \pi_i^n)$$

with n being the number of the intraday session in which the wind power producer participates. This fact did not affect the overall results as the imbalance term (cost/revenues) met the criteria of not being economically more advantageous than the intraday bidding update.

The test case results originate from a wind power plant with 20 MW installed. The selected test period was 2007, and the optimisation and simulation of the new imbalance price scheme was programmed in Matlab. Furthermore, once the discretisation was performed, a value of bin power was considered. Then, a value of 20 power bins was selected, and a dynamic value was selected for imbalance price bins, which depended on the maximum historical prices values for every hour. In the new IP scheme proposal, the generated values were employed as historical data to estimate values for the imbalance prices to run the simulations in a realistic manner.

To analyse the results, some variables are compared.

- Revenues (€): Incomes obtained by a wind power producer resulting from its market participation.
- Power Error (MW): difference between power bid at intraday market gate

closure ($P_{i,t}$) and power delivered to the power system ($P_{g,t}$).

$$\Delta P_t = P_{i,t} - P_{g,t} \tag{C.11}$$

- Absolute Power error (MW): power error absolute value.

$$|\Delta P|_t = |P_{i,t} - P_{g,t}| \tag{C.12}$$

The average hourly value is provided in terms of both power error and absolute power error. In the next sections, the results are presented and discussed.

C.7.1 Reference cases A and B

To compare the simulations obtained with these tests, two reference cases based on power predictions were employed. In fact, the usual strategy adopted by wind power producers when bidding to the Spanish electricity market is to use the best prediction available; consequently, these reference cases may be used to simulate habitual behaviour. The cases employed as references were

- **Reference case A (DM)** Point prediction in daily market. The wind power producer bids the last prediction available at gate closure time to the daily market, i.e., with a time horizon from 14 to 38 hours. That is, the wind power producer does not participate in the IM.

- **Reference case B (Best)** Point prediction in daily and intraday markets. The wind power producer updates the prediction made to the DM in the IM when forecasts with higher accuracies are available because of its shorter time horizon.

An approach based on deterministic predictions was employed in both cases. Both strategies were evaluated with the actual and proposed imbalance prices scheme, previously described in Sections C.6.1 and C.6.2, respectively. Then, as the imbalance prices are different in any case, diverse results for incomes were obtained. By contrast, as these strategies were based on deterministic predictions, the errors and absolute errors were identical in employing the prices of both the current and proposed imbalance prices schemes. The simulation results are presented in Table C.4.

		Case A: DM	Case B: Best
Revenues (M€)	Current IP	1.3685	1.3924
	Proposed IP	1.3479	1.3782
Error (MW)		0.2098	0.094
Absolute Error (MW)		2.4963	1.7874

Table C.4: Test results in DM and Best reference strategies

C.7.2 Case C: current imbalance price scheme

In this case, a risk-constrained optimisation strategy is applied, which follows the mathematical formulation presented in Section C.5.1. Any CVaR value represents the minimum incomes required by producers, and diverse risk attitudes can thus be modelled, assessed and compared.

The results originating from applying diverse CVaR restrictions are presented in Table C.5. All of the results were based on a confidence interval of 0.95. The parameters evaluated in the simulation are described above. Apart from the CVaR simulations, in the last column, the simulation outcomes with no CVaR restrictions are included.

	CVaR (€) [β=0.95]				
	100	500	800	1200	No CVaR
Revenues (M€)	1.3799	1.3892	1.3922	1.3924	1.4028
ΔP (MW)	-0.6386	0.0753	0.094	0.094	0.7975
$\lvert\Delta P\rvert$ (MW)	2.928	1.8099	1.7886	1.7874	3.0327

Table C.5: Results comparison of CVaR (β=0.95) for present imbalance prices scheme

The latter results indicate that as the CVaR value increases, the obtained revenues asymptotically approach the revenues obtained following reference case B, i.e., to bid the point prediction in the IM. However, the maximum income worth is obtained when no CVaR restrictions are applied and, thus, when higher errors occur. Then, it is more profitable to have a risky attitude: applying a risk management strategy does not improve the economic results in the raised optimisation problem.

C.7.3 Case D: imbalance price scheme proposal

In this section, a new regulation for imbalance prices, which was explained in Section C.6.2, is considered. An analysis of the consequences of applying these new rules in wind power producers is performed for unlike CVaR cases. This procedure allows us to run simulations with a different attitude towards risk, and it selects diverse power bids and consequently produces diverse errors. In addition, because wind power producers follow an optimisation strategy when bidding to the market, the effects of different imbalance prices schemes have been tested. Thus, the sensitivity of wind power producers to market prices is analysed, and how IP schemes can enhance the reduction of deviations with adequate market signals is studied.

The simulation results are presented in Table C.6. Compared with the out-

	CVaR (€) [β=0.95]				
	100	500	800	1200	No CVaR
Revenues (M€)	1.3301	1.3701	1.3772	1.3782	1.3481
ΔP (MW)	-0.9033	-0.0112	0.0839	0.094	0.3615
$\lvert\Delta P\rvert$ (MW)	2.6003	1.8506	1.7931	1.7874	2.4624

Table C.6: Results comparison of CVaR (β=0.95) for the proposed imbalance price scheme

comes of the present regulation, under the new imbalance prices scheme, optimisation strategies incur lower power errors. Strategies for the same level of CVaR are computed in an identical manner; the differences lie in the distinct imbalance price values. As these strategies are based on price forecasts, they have a tendency to reduce their errors when the prices are correlated with them. This tendency is especially important in cases that are prone to risk, such as non-constrained optimisation strategies and low CVaR values, i.e., the cases that incur greater deviations. An asymptotic tendency of the incomes to reach the value of the reference case 'Best' is observed again.

It can be observed that the reference case incomes are lower in the proposed imbalance pricing scheme than in the current imbalance pricing. Although these strategies follow a behaviour based on forecasts, they are penalised due to the deviation from the initial schedule. This fact is apparently contrary to the integration of wind power in the power system, as it does not enhance the market participation; however, these regulations would dissuade the use of arbitrage strategies in DM, which could occur, though they are unlikely situations. Weber [30] recommends avoiding the use of ancillary services to foster intraday markets liquidity. Along the same lines, in other countries, some regulation policies impose additional penalisations to producers that use ancillary services.

Apart from the aggregated analysis presented in Table C.6, a more in-depth study of the effect on errors of modifying the imbalance price scheme is presented in Fig. C.1. In this graph, a histogram comparing the errors under diverse CVaR

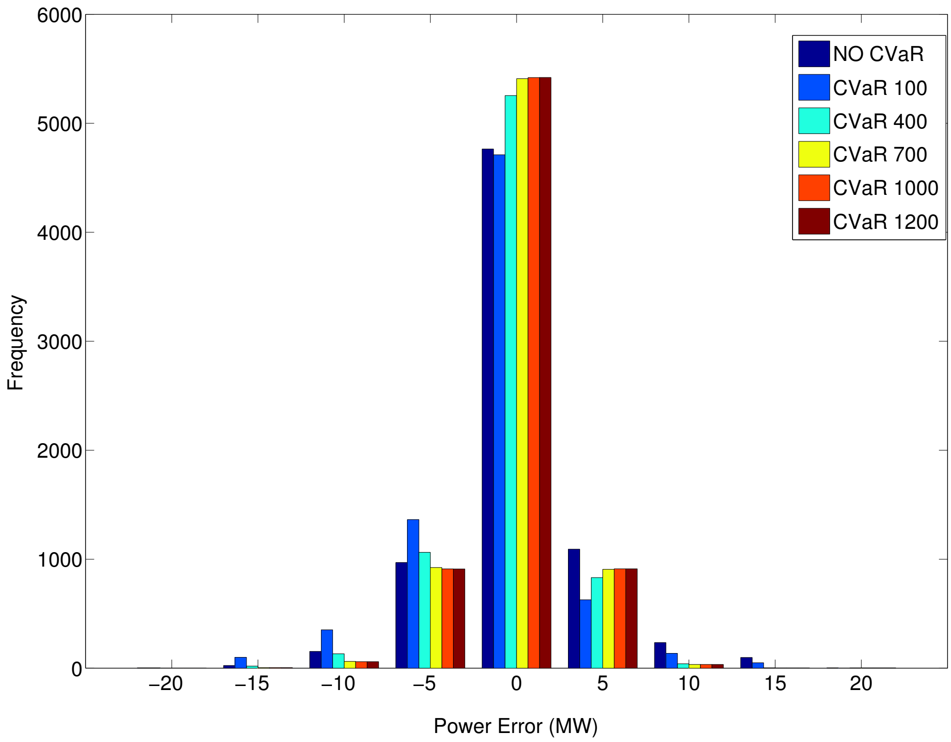

Figure C.1: Histogram of power errors for imbalance price proposal test cases parameters is displayed. It can be appreciated how constraining minimum revenues value has an effect on incurred power errors using the optimal strategies. In terms of power errors, the more severe restrictions, i.e., higher CVaR, deviation dispersion decreases. Thus, the sum of the absolute error globally decreases when CVaR restrictions are applied, as observed in Table C.6. In short, to apply a CVaR restriction to revenues reduces deviations, as the new IP scheme penalises risk-prone strategies that incur higher errors.

C.7.4 Results comparison

First, the income distributions obtained using the former strategies were analysed. For this, in Fig. C.2, the income distributions are displayed as follows:

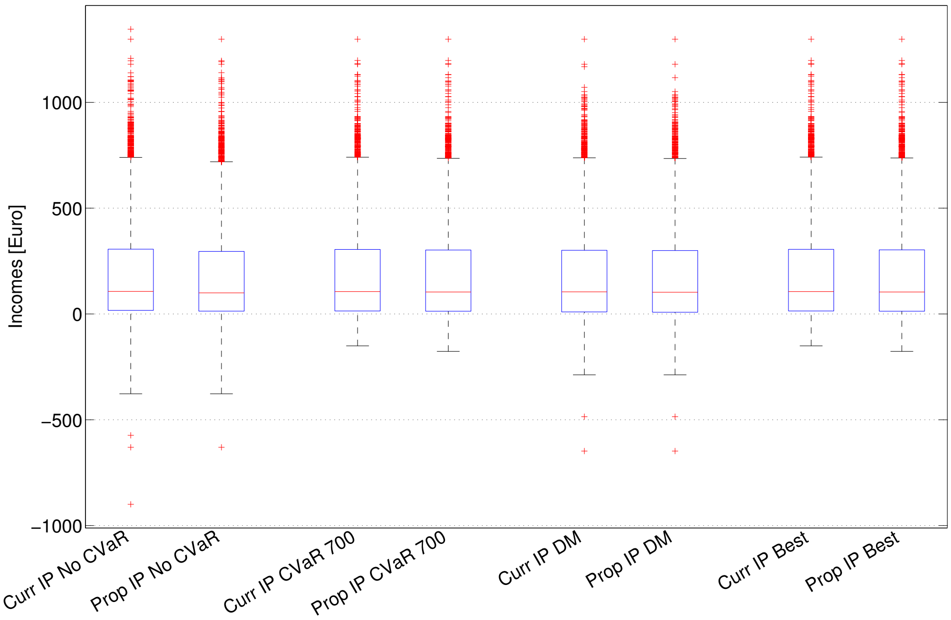

Figure C.2: Income comparison for the current and proposed IP scheme

1 Optimal strategy without CVaR constraint, applying the current IP scheme.

2 Optimal strategy without CVaR constraint, under the proposed IP scheme.

3 Case C, optimal strategy with CVaR (700 €), under the current IP scheme.

4 Case D, optimal strategy with CVaR (700 €), under the proposed IP scheme.

5 Reference case A 'DM', under the current IP scheme.

6 Reference case A 'DM', under the proposed IP scheme.

7 Reference case B 'Best', under the current IP scheme.

8 Reference case B 'Best', under the proposed IP scheme.

For strategies 3 to 8, in which the errors are relatively low, the income distributions are similar under both regulations, although those obtained with the new proposal are slightly smaller. In the first cases 1 and 2, i.e., when a bidding strategy without CVaR restriction is employed, it can be appreciated that extreme losses occur less frequently than in the current imbalance price scheme, i.e., the probability of occurrence of extreme losses is reduced with the proposed imbalance prices scheme for producers who use optimisation strategies based on prices.

Second, the power error distributions are presented in Fig. C.3, where plots represent power errors for strategies:

1 Optimal strategy without CVaR restriction, applying the current IP scheme.

2 Optimal strategy without CVaR constraints, following the proposed IP scheme.

3 Case C simulation with CVaR equal to 700 €, applying the current IP scheme.

4 Case D simulation with CVaR equal to 700 €, following the proposed IP scheme.

5 Distribution of power deviations because of bidding the best prediction available at DM closure time.

6 Distribution of power errors when bidding the best prediction available at IM closure time.

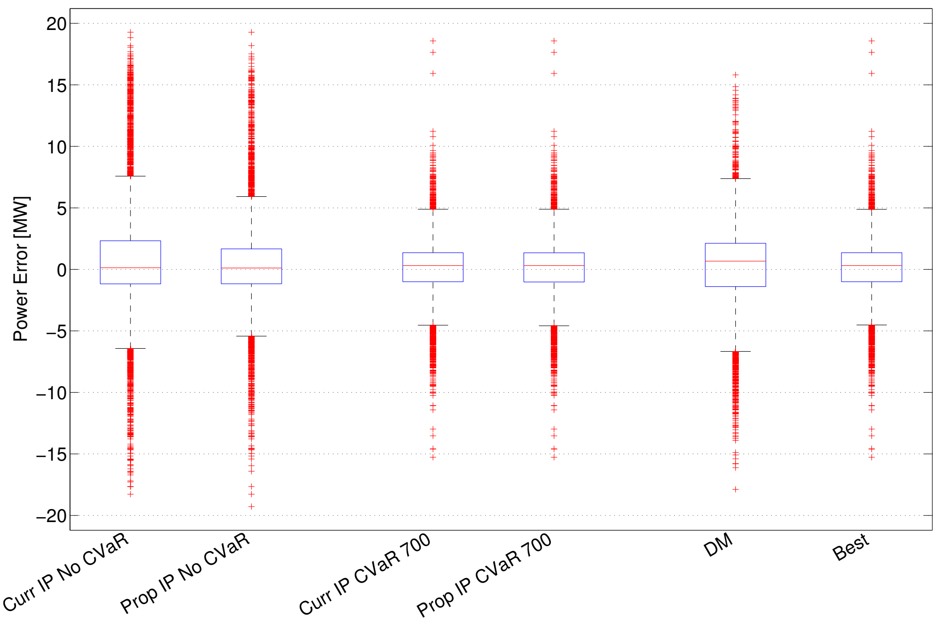

Figure C.3: Power errors comparison for the analysed strategies

From the boxplots, we can appreciate the effect of the new regulation on power error distributions in comparison with deviations originating from strategies based on forecasts. The whiskers correspond to the 25 and 75 percentiles of the distribution. In graphs 1 to 4, the odd distributions correspond to the current regulation in the Spanish electricity market, and the even distributions represent the IP regulation proposal. It can be appreciated that even boxplots have lower dispersion and that the frequency of deviations is smaller; moreover, extreme errors are less frequent. Therefore, applying a more severe regulation to penalise power deviations will foster the reduction of errors. The errors are more clustered when the new IP scheme is applied, as in boxplots 2 and 4, compared with the DM strategy, although the outliers have greater dispersion but are partially lower than in analogous cases with the present IP scheme, i.e., boxplots 1 and 3.

To analyse the relationship of aggregated deviations and incomes, Fig. C.4 is presented. In this figure, the incomes vs. absolute power error average values are

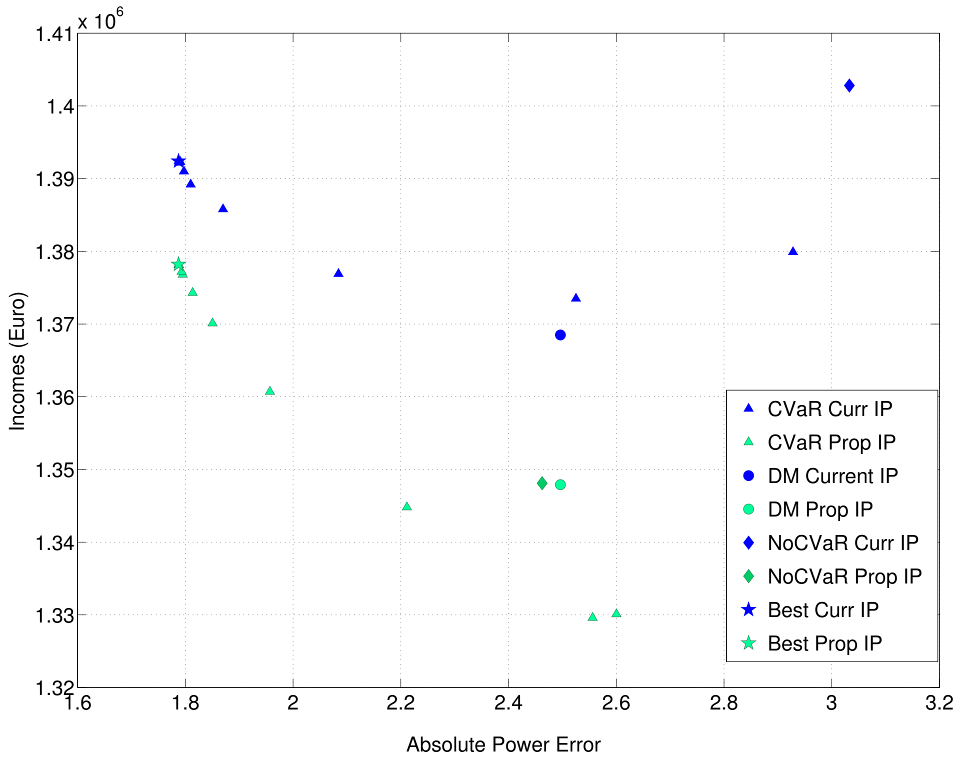

Figure C.4: Incomes vs. Absolute Power Error

represented for both cases C and D. The dark symbols correspond to the current IP scheme (case C), while the light markers represent the proposed regulatory scheme (case D). Moreover, triangles depict CVaR strategies, diamonds depict optimisation strategies without CVaR restrictions, circles depict DM and stars depict Best.

Based on the results of case C regulation, i.e., the current IP scheme (dark symbols), while the incomes are correlated with absolute errors for diverse CVaR values and reference cases, this dependence is not observed in the optimisation without CVaR, where it can be appreciated that higher incomes have been obtained despite causing the highest absolute power errors. Thus, obtaining better revenues could be based more on obtaining better price forecasts than on producing less power errors. In fact, in this regulation, the best economic results are not those that produce less deviations to the power system, as can be appreciated in Fig. C.3, where boxplot 1 possesses the highest power errors dispersion. Hence, optimisation strategies result in bigger revenues, although they also produce higher deviations. Focusing on the tendency of optimisation strategies, i.e., CVaR cases, a slight correlation exists between reducing errors and increasing revenues, except in those cases with larger absolute higher errors, No CVaR and smaller CVaR values (100 to 300 €), i.e., cases with more risky attitudes.

In case D regulation (pale markers), there is a linear correlation between absolute errors and revenues, which fulfils the CVaR optimisations. In this regulation, the maximum incomes are those associated with the smallest power deviations (Best prediction). In these cases, some atypical values that do not meet the relationship between incomes and power errors can be observed in the DM reference cases and No CVaR optimisation strategy. As observed in Fig. C.3, higher extreme values for short imbalances occur in boxplots 2 and 5. Because buy imbalance prices, π^{buy}, are not bounded, short deviation imbalance costs can be very high and the revenues will thus be lower than in other cases. In conclusion, the reduction of short power errors leads to higher incomes. Moreover, the results indicate that test cases D have a better response to market signals, as the deviations were reduced in comparison with test cases C, when both cases follow the same optimisation strategy.

From the comparison of both regulations, it can be deduced that the proposed regulation fosters a reduction of deviations. This behaviour can be extended to any generator because market participation is not exclusive to wind power producers. Therefore, the generators pay limited penalties for schedule deviations. In conclusion, IPs are not adequate market signals, as the generators are not sensitive to power deviations; balancing signals are therefore not cost-reflective, as they do not induce efficient behaviour. This imbalance pricing scheme allows generators to obtain benefits based on price predictions instead of fostering the diminution of power imbalances. Therefore, this regulation could incentivise market participants to over-use balancing services, which will debilitate the regulation efficiency.

C.8 Conclusion

From the simulations run and under the assumed hypothesis, the following conclusions may be drawn:

- Applying CVaR restrictions to revenues reduces deviations in the power system.
- The regulation of the imbalance prices may not be adequate for the Spanish electricity market because an error drop is not sufficiently encouraged. The incomes obtained by the wind power producers are not completely correlated with their contribution to the overall power deviations. Indeed, in the test case, higher deviations imply higher incomes.
- To improve the effectiveness of imbalance prices, we suggest the application of a new imbalance price scheme, which includes an additional constraint to avoid those cases in which deviations are not correctly penalised in an effort to prevent benefits from being based on price predictions instead of power predictions.

Acknowledgments

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Appendix D

Assessing the economic benefit of a bidding decision support tool for wind power producers

Abstract

This document describes the assessment of a decision support tool for wind power producers in real wind farms. This tool allows them to update their positions taken in daily markets into subsequent adjustment markets. The tool intends to maximize the revenues of wind power producers that participate in electricity markets through an optimization procedure, making use of the possibilities of non-continuous adjustment markets and the probabilistic tools developed in the EU project ANEMOS.plus. Results are presented for nine Spanish wind farms and they are compared to those obtained with a standard strategy of market participation for wind power producers. For the examined cases, the revenues were overall increased in a 1.3% by using the decision support tool. This could encourage even more the participation of wind energy in electricity markets. The overall energy imbalance also increases, showing a potential risk for the whole system if all wind power producers would use such a tool.

D.1 Introduction

The penetration of wind generation in power systems is increasing worldwide and also its participation in electricity markets is encouraged by different regulatory authorities as a way to achieve a smoother integration of this renewable resource into the power system. This participation usually requires a forecast of the future wind production, which is done by means of prediction tools that provide an estimate of the hourly average production for the next hours.

These prediction tools are inaccurate and when generators contract to sell power in spot[1] markets, imbalances between the contracted volume and actual output must be rectified in the real-time market, which means economic losses over the sale of the energy in the spot markets. These losses may reach the 10% of the wind farm market revenues, that can be found in studies by Bathurst et al. [11], Fabbri et al. [9], Holttinen [10], Angarita-Márquez et al. [16]. Several approaches to handle the uncertainties of renewable power generation can be found in literature, such as those reported by Nielsen et al. [91], Anvari Moghaddam & Seifi [92], Catalão et al. [93], Soroudi & Afrasiab [94], Soroudi [95].

One possibility of reducing the imbalance costs is through the consideration of aggregated wind power, as can be found in studies by Giebel et al. [96], Mohammadi et al. [97]. Another possibility is to update the prediction in the adjustment markets that take place in almost every electricity market. Since the accuracy of the prediction tool decreases for larger prediction horizons, updating wind power market position implies trading in these adjustment markets, and, since the prices in these markets usually take the same level than those of daily markets, this means no losses in the long run.

However this participation is usually made under certain conditions. First, a prediction tool with frequent updates, in particular, before the closing of the adjustment market, should be available. Then, this market should be liquid enough to allow the trading, and finally it should be marginal, i.e., the energy must be traded at a single marginal price, so that wind energy producers could participate as price taker producers. The first condition is easily implemented in most of present prediction tools and the last two conditions are fulfilled by the Spanish

[1] The European convention is adopted in this paper; in the USA the term forward markets is used.

intraday market, which has been considered as framework for the study.

If the goal is improving the wind power producer revenues, the best way of participating in the adjustment market is by means of optimization tools that obtain the optimal amount of energy to be traded in this market. To do this, it is necessary to consider the uncertainties of the process, namely the production of the wind farms, the adjustment market prices and the imbalance prices. How can this be made is explained in the body of this paper.

Different approaches to this problem have been already made in technical literature. References by Pinson et al. [70], Usaola & Angarita [17], Conejo et al. [98] explored the advantages of considering the uncertainty of wind power predictions. The market position update in the intraday market was explored by Fabbri et al. [9], Holttinen [10], Usaola & Angarita [17], Usaola & Moreno [18]. The important problem of the correct estimate of the imbalance prices was considered in different ways. Holttinen [10] used already known imbalance prices. In other cases, reserve prices (Fabbri et al. [9], Matevosyan & Soder [20]) or average imbalance prices (Usaola & Moreno [18]) were used. These are rough simplifications of reality, and further advances in a more proper modelling were presented by Bueno et al. [1]. Morales et al. [15] makes a detailed modelling of a probabilistic optimization method, including risk-averse preferences, but the simulation was only for a short period of time and the results were not checked with real cases. Risk-averse strategies have been also considered by several authors, such as Dent et al. [24], Pousinho et al. [84], Dukpa et al. [76], Moreno et al. [2].

In all these references the probabilistic optimization tools improved the results of traditional methods, reducing the wind power producer imbalance losses, but in a previous work by Moreno et al. [2] we showed that the inclusion of risk constraints did not improve the economic results of wind power producers, nor was of benefit to the system, since the imbalances were not diminished. Taking into account those results, the present work aims at assessing the economic benefits of a decision support tool based on a risk-neutral strategy in real cases and intends to extract conclusions about the actual performance of markets. The conclusions will be supported by results produced from a long evaluation period in nine real wind farms.

The paper is organized as follows. Section D.2 describes the electricity market design and how wind power producers participate in it. Section D.3 describes the problem and presents the optimal bid strategy. This strategy is implemented in a trading decision support tool, described in Section D.4. Section D.5 presents the case study and discusses numerical results. Finally, in Section D.6, conclusions are drawn.

D.2 Participation of a wind power producer in the electricity market

D.2.1 Overview of the market design

The Spanish electricity market is organized in several markets. In this work, two successive spot markets are considered: a day-ahead market (named *daily market*) and an adjustment market (named *intraday market*). Participants in the daily market can submit their bids until 10:00 a.m. of the trading day, d, for the hourly average power delivered in the 24 hours of the subsequent day (*operating day*, $d{+}1$). The price is set, according to a uniform-price auction, equal to the highest accepted supply bid (the so-called *system marginal daily price*, MDP). After the closure of the daily market, participants can update their positions in the intraday market according to new information and/or availability. The intraday market is also a spot market currently structured into 6 trading sessions with different schedule horizons, from 28 hours to 9 hours. Participants in the intraday market can present their offers for selling or purchasing energy with a minimum notice of 3 and a quarter hours before the delivery takes place. Trading is organized as uniform-price auctions in which the market operator determines the clearing prices (which are referred to as the *intraday marginal prices*). Thus market participants receive/pay the intraday marginal prices, if their sale/purchase bids are accepted. The timetable for daily and intraday market sessions is given in Table D.1. The fact that the intraday market takes place six times a day, instead of being a continuous market, allows it more liquidity, as pointed out by Weber [30]. Specifically, the total traded energy in the intraday market added up to 35,338 GWh (18% of the day-ahead market) in 2010, as reported by Furió [99].

Once wind power producers have fine-tuned their positions in the intraday markets, imbalances between the contracted energy volume and actual output will

	Daily Market	Intraday Market					
		1^{st} ses.	2^{nd} ses.	3^{rd} ses.	4^{th} ses.	5^{th} ses.	6^{th} ses.
Session opening		16:00 (d)	21:00 (d)	01:00 (d+1)	04:00 (d+1)	08:00 (d+1)	12:00 (d+1)
Session closing	10:00 (d)	17:45 (d)	21:45 (d)	01:45 (d+1)	04:45 (d+1)	08:45 (d+1)	12:45 (d+1)
Schedule horizon	24 h 1-24 (d+1)	28 h 21-24 (d) 1-24 (d+1)	24 h 1-24 (d+1)	20 h 5-24 (d+1)	17 h 8-24 (d+1)	13 h 12-24 (d+1)	9 h 16-24 (d+1)

Table D.1: Daily and intraday markets timetable in the Spanish system.

be rectified in the real-time market. The imbalance settlement in Spain follows a dual imbalance pricing mechanism, as indicated by ETSO [71]. The basic rule is that a 'main price' is applied to imbalance volumes in the same direction as the overall market, whereas a 'reverse price' is applied to imbalance volumes opposite in direction to the overall market. The 'main price' is derived from energy balancing actions and the 'reverse price' can be determined by reference to a power exchange (the case of Spain) or be based on the prices of the balancing actions in the reverse direction during the settlement period. Hence, the charges for those who incur in imbalances depend on the system overall imbalance, and on their own imbalance (volume and direction). Table D.2 shows the rules followed by the Spanish market for the imbalance prices, where 'MDP' stands for the marginal daily price and 'WAPD'/'WAPU' are the weighted average price for down/up energies in balancing actions.

		SYSTEM	
		LONG	SHORT
GENERATOR PRODUCTION	LONG	min(MDP,WAPU)	MDP
	SHORT	MDP	max(MDP,WAPD)

Table D.2: Imbalance prices in the Spanish electricity market.

D.2.2 Revenues of a market participant

We consider a wind power producer that participates in a three-settlement (daily, intraday and real-time) system and the following assumptions:

- The market is a pool with marginal prices. This is valid both for the daily and for the intraday markets.
- The bids from wind power producers are always accepted[2].
- The intraday market is sufficiently liquid.
- The wind power producer updates the hourly production only once, in the latest intraday market session available.
- The subsidy for wind energy is not considered, since it is paid to the actual energy produced, which is not changed at any time.

Under these conditions, the revenue R_t obtained by a wind farm participating in the electricity market in a settlement period t is a random variable that depends on other random variables, namely the power production $P_{g,t}$, the intraday marginal price $\pi_{i,t}$ and the imbalance prices, π_t^{up}/π_t^{down}. The revenue R_t is given by the following expression:

$$R_t = P_{d,t}\pi_{d,t} + \pi_{i,t}(P_{i,t} - P_{d,t}) + I_t \tag{D.1}$$

where I_t is the *imbalance term*, defined by

$$I_t = \begin{cases} \pi_t^{up}(P_{g,t} - P_{i,t}) & P_{g,t} > P_{i,t} \\ \pi_t^{down}(P_{g,t} - P_{i,t}) & P_{g,t} < P_{i,t} \end{cases} \tag{D.2}$$

which may be an income resulting from the balancing process, if positive energy deviation is given, or a cost, for the negative energy deviation.

The meaning of the different terms of the equations, for the considered period t, is:

[2] Wind power producers act as price takers. They bid for selling a given amount of energy at zero price and for buying energy in the adjustment market at the maximum price (according to regulations, the highest price allowed for a purchase bid in the Spanish market is 180.1 €/MWh).

- $P_{g,t}$. Power actually generated by the wind farm.
- $P_{d,t}$. Power committed by the wind farm in the daily market. It coincides with the prediction available at the gate closure of that market.
- $P_{i,t}$. Power committed by the wind farm in the intraday market.
- $\pi_{d,t}$. System marginal price of energy (in the daily market).
- $\pi_{i,t}$. Intraday marginal price of energy.
- π_t^{up}. Imbalance price for a positive energy deviation (wind power production long).
- π_t^{down} Imbalance price for a negative energy deviation (wind power production short).

Typically, at any period t, $\pi_t^{up} \leq \pi_{d,t} \leq \pi_t^{down}$, and imbalance prices may be written as

$$\begin{aligned} \pi_t^{up} &= \alpha_t^{up} \pi_{d,t} \\ \pi_t^{down} &= \alpha_t^{down} \pi_{d,t} \end{aligned} \tag{D.3}$$

Thus, the revenue R_t in a settlement period t may be rewritten as

$$R_t = P_{d,t}\pi_{d,t} + \pi_{i,t}(P_{i,t} - P_{d,t}) + \begin{cases} \alpha_t^{up}\pi_{d,t}(P_{g,t} - P_{i,t}), & P_{g,t} \geq P_{i,t} \\ \alpha_t^{down}\pi_{d,t}(P_{g,t} - P_{i,t}), & P_{g,t} < P_{i,t} \end{cases} \tag{D.4}$$

D.3 Overview to the optimization method

Therefore, a main decision must be taken by any market participant: how much power to bid in the daily and in each intraday market. As already mentioned, wind power producers behave as price takers.

The amount of wind power bid usually comes from a deterministic forecast, which is, in general, more accurate when the time horizon is smaller. Hence, there will likely be a better forecast for the intraday market than for the daily market. The most accurate prediction, however, does not lead to the highest revenues, due to the different prices of reserve energy in the imbalance process, and to the bias of the prediction programs. Then, if the aim is maximizing the revenues and not minimizing the energy imbalance itself, the prices of trading and the imbalance prices should be considered as well for an optimal performance.

Looking at (D.4), both the daily market bid and the intraday market bid may be considered as variables of the optimization method. Nevertheless, since forecasts for daily market are obtained with many hours in advance (typically between 15 and 38 hours), their large uncertainties would not yield better solutions and their consideration would increase very much the computation time and the complexity of the problem. Thus, only the intraday market bid is considered as a variable in the optimization problem.

Therefore, once a bid has been presented in the daily market, to update it in the intraday market requires choosing between trading in this market and the possible imbalance cost. Since, at the moment of taking this decision the prices are not known, they should be estimated somehow. The actual power generated at the operational settlement time, and the imbalance itself, are not known either, so the decision depends on these uncertain estimations: intraday price, imbalance price and imbalance volume.

Hence, an optimal decision should take into account forecasted values of these magnitudes, and, if available, the uncertainties of these forecasts. This would provide a tool that will be intended to maximize the revenues of the market participant.

The adopted solution consists in producing bids for the intraday markets that take into account:

- The uncertainties of the short term wind power predictions.

- A new tool which forecasts the intraday marginal prices.

- An estimate of the future imbalance prices.

This new strategy has been applied to nine wind farms in order to assess the potential benefits in real systems.

		DAY D-1															DAY D																							
		10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
DAILY MARKET		X															15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38
INTRADAY MARKET	S2													X			3	4	5	6																				
	S3																	X			3	4	5																	
	S4																				X			3	4	5	6													
	S5																								X			3	4	5	6									
	S6																												X			3	4	5	6	7				
	S1 (same day)																																	X			3	4	5	6

Table D.3: Times for updating bids in the intraday market sessions.

D.3.1 Bidding strategy description

The problem considered here is the optimization of the intraday market bid, given a certain position in the daily market, and taking into account the uncertainties of the involved random variables. Participation in the daily market is assimilated to the sale of the predicted power production for the wind farm, available at the time of gate closure.

In this context, the position previously taken in the daily market for each hour 'h' is updated only once in the intraday market, using the latest session available for the considered hour 'h'. Thus, the schedule for updating bids for day D is made following the rules of Table D.3, which follows those of the Spanish electricity market (OMEL [33]). In it, the daily market has its gate closure at 10:00h, and therefore the bids for the daily market have a lead time between 15 and 38 hours. The lead time for the 6 existing intraday market sessions varies from 3 hours until 7 hours. The 'X' represent bidding times and the numbers inside the cells indicate the prediction horizon needed.

The aim of the problem is to obtain the optimal position in the intraday market $P_{i,t}$ that maximizes R_t. Since the optimization problem is independent for each period of time t (usually an hour), this subscript will be dropped hereon.

D.3.2 Objective function and problem solution

Mathematically, the revenue R can be expressed as a function of the generated power (P_g), the intraday marginal price (π_i) and the imbalance prices ratios (α)

$$R = g(P_g, \pi_i, \alpha; P_i) \tag{D.5}$$

where α represents both α^{up} (if $P_g \geq P_i$) and α^{down} (if P_g P_i).

The expected revenue for the hour considered will be, then,

$$\overline{R} = E[R; P_i] = \int_{-\infty}^{\infty} R\, f(R) dr = \int \int \int g(P_g, \pi_i, \alpha; P_i) f(P_g, \pi_i, \alpha)\, dP_g\, d\pi_i\, d\alpha \tag{D.6}$$

where $f(R)$ is the Probability Density Function (PDF) of the random variable R. If the random variables, P_g, π_i and α, are considered independent, then it may be written that

$$f(P_g, \pi_i, \alpha) = f_{P_g}(P_g) f_{\pi_i}(\pi_i) f_\alpha(\alpha) \tag{D.7}$$

where $f_{P_g}(P_g)$, $f_{\pi_i}(\pi_i)$ and $f_\alpha(\alpha)$ are the PDFs of the random variables P_g, π_i and α, respectively.

The uncertainty of the intraday prices has not been considered because it does not improve the results, due to the high symmetry of the PDF of forecasts' uncertainty, but increases the computation time. Consequently, deterministic forecasts for the intraday marginal prices are considered, and therefore, the expected revenue for a specific hour may be simplified

$$\overline{R} = E[R; P_i] = \int \int g(P_g, \alpha; P_i) f_{P_g}(P_g) f_\alpha(\alpha)\, dP_g\, d\alpha \tag{D.8}$$

The optimization problem can be posed, then, as

$$P_{i,opt} = \arg \max_{P_i} E\left[R; P_i\right] \tag{D.9}$$

with $P_{i,opt}$ being the optimal position to be taken in the intraday market. This problem may be solved easily by simple enumeration, and it must be solved for each time interval. In order to make this, it is necessary to discretize the range of the possible values offered.

D.4 Trading decision support tool

The aim of the tool is to provide the optimal bids for the next session S of the Spanish intraday market of day D, according to timetables given in Table D.1 and Table D.3, maximizing the revenues.

For this purpose the following input data are necessary:

- Historic data (for at least the previous two months):
  - Daily and intraday market prices [€/MWh].
  - Imbalance prices (up/down) [€/MWh].

  These data are used to generate forecasts for future intraday marginal prices and to estimate the uncertainty of future imbalance prices (up/down). The intraday marginal price forecasting issue is addressed through a specific tool based in a time series model, as explained by Bueno et al. [1]. The uncertainty of the imbalance prices has been modelled from the hourly frequency distribution observed from the historic data (taking a two-month moving window). As the marginal price of the daily market is known when the bids for the intraday markets must be made, and imbalance prices are indexed to that price, instead of the prices themselves, the parameters α^{up} and α^{down} have been actually used. Then, a different PDF is used for down imbalance prices α_h^{down} and for up imbalance prices α_h^{up} at each hour of the day. The reader can find further detail about the probabilistic imbalance price modelling in the study by Bueno et al. [1].

- Present data:
  - System marginal prices for day D (hourly prices available on day $D-1$).
  - Intraday marginal prices for the previous session $S-1$ (hourly prices available on day $D-1$ or D, depending on the session).
  - Last values of imbalance prices (hourly up/down prices in day $D-2$).
  - Wind power predictions with uncertainties (from ANEMOS platform):
    - Wind power predictions for the selected wind farms with a time horizon of 40 hours, produced by ANEMOS [MW].
    - Uncertainty of wind power predictions [MW], provided by the ANEMOS added-value tool, in form of quantiles (from 0 to 1, in steps of 0.05).

The outputs are:

- Optimal bids [MW] for the 3-5 first hours in the next intraday market session gate closure (session S of day D).

- Hourly expected revenues, in €, with the proposed strategy and with other conventional strategies if desired, in order of comparing results.

The price data come from public web sites (OMEL [33], E-sios [34]), and will be taken by the tool as text files. Output is given in the same text format. The block diagram of the trading decision tool is depicted in Figure D.1. Energy price forecasts for the 3-5 hours of interest, in the next intraday market session, are generated in the Intraday Market (IM) Prediction Module from the historic and present price data. Also an estimate for the hourly PDF of imbalance prices (up/down) is performed at the Imbalance Prices Estimation Module. Those new data, together with wind power data (forecasts and uncertainties) provided by ANEMOS, enter into the Optimal Trading Module to generate the optimal bids for the next intraday market session and the expected revenues.

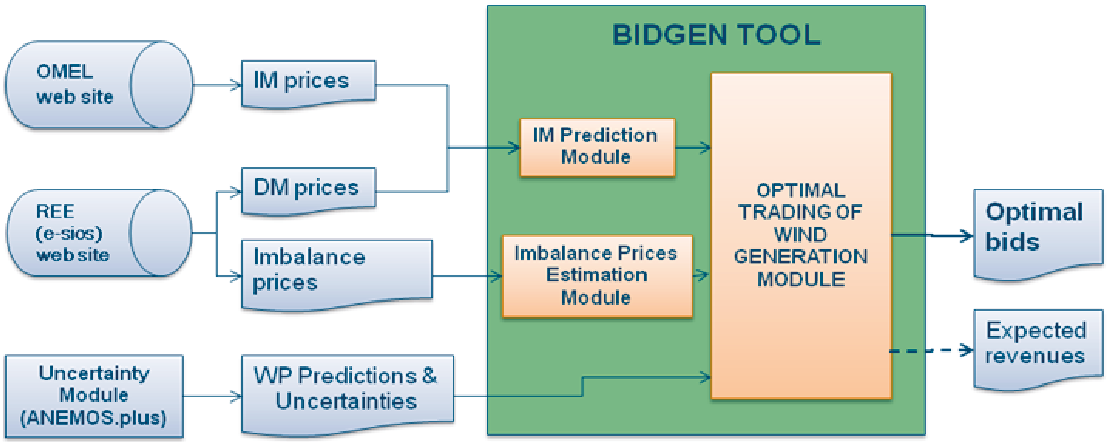


Figure D.1: Block diagram of the trading tool

Summarizing, the trading decision support tool has been designed to run in real time, using the actual prices of daily market and wind power prediction and uncertainties from a probabilistic wind power forecasting tool such as the one of ANEMOS.plus. The trading tool includes a prediction tool of intraday market prices and a module for estimate the uncertainty of imbalance prices.

D.5 Case study

D.5.1 Description of the physical system and data

The bidding tool has been tested for nine Spanish wind farms chosen in 5 different regions over the Spanish geography, as seen in Figure D.2. The total installed power[3] is 317 MW.

For each individual wind farm, the actual production along 2010 was given together with the stochastic forecasts of that production. No aggregated data was provided.

Figure D.2: Geographical distribution of the 9 wind farms chosen.

D.5.2 Evaluation method

The benefits of the proposed method will be assessed comparing the results of the probabilistic tool (*proposed method*) with the results of a participation in the electricity market using point predictions (*standard method*), which is commonly used by wind power producers. This evaluation method is easy to understand and implement.

[3] The installed capacity of each wind farm is given in Table D.5, with the numerical results of the method.

Thus, an evaluation tool has been developed, which uses, as inputs, actual market data (intraday marginal prices and imbalance prices), the actual energy generated by the chosen wind farms, the energy contracted on the daily market, i.e. the best forecast (wind power point prediction) available, and the optimal bids generated by the bidding tool.

The evaluation tool computes, for each wind farm, the revenues obtained by a point prediction strategy (updating bids in intraday markets with shorter horizon forecasts) and revenues obtained with the optimal strategy. Deterministic wind farm power predictions are provided using the ARMINES AWPPS model (Nielsen et al. [91]), which has a good performance in the first horizons. From these values and the ANEMOS uncertainty module, the uncertainty of the wind power prediction is found.

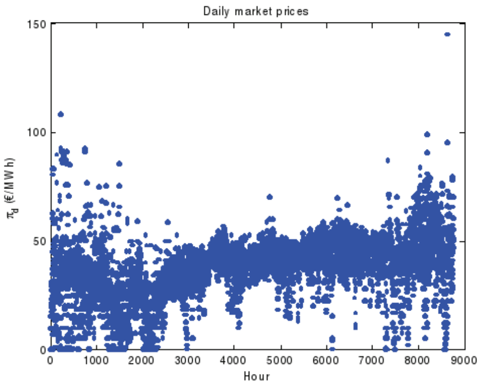
The output data of the evaluation tool are the potential revenues obtained with both strategies (point prediction and optimal) and the potential benefits of the optimal strategy.

The expected benefit is the improvement of the total revenues in the trading of wind power generation in the electricity market, so the potential results will be of interests for wind power producers in general.

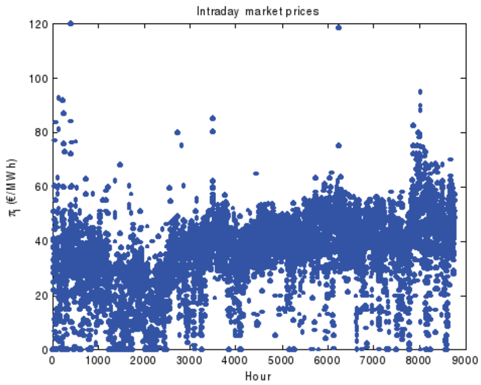
D.5.3 Price data

The method has been tested for the whole year 2010 (8760 hours). Spanish energy prices were very variable in that year, from very low values (0 €/MWh) to high values (near 150 €/MWh). Hourly prices in the daily and intraday markets are exhibited in Figure D.3 and their respective price duration curves are shown in Figure D.4.

Some relevant features of these prices are presented in Table D.4. The number of hours with zero prices is noteworthy. In this case, these prices were motivated by low demand, high rain and consequently hydro power, and high wind power. Although not usual in the Spanish market, this situation of very low prices may become increasingly frequent with greater wind energy penetration, and may affect negatively to the performance of the intraday market price prediction tool, as can be observed in Figure D.5 where different values are obtained as forecasts of an actual zero price. The solid line in Figure D.5 represents a linear fit to the data



(1) Daily market



(2) Intraday market

Figure D.3: Hourly prices in the daily and intraday Spanish market (year 2010).

	Mean value (€/MWh)	Maximum value (€/MWh)	Hours with zero price
Daily market	37.01	145	331
Intraday market	34.09	119.85	448

Table D.4: Spanish electricity market prices features (year 2010).

and the dashed line represents perfect forecasts. The distorted effect of a zero price is clear comparing both lines. For low prices, the tool has a tendency to the over-prediction but for high prices, it tends to under-predict. The distribution of the errors is asymmetrical, with mean in the value -0.96 and a standard deviation of 7.61. Although the performance of the intraday market price prediction tool may be improved, it is considered acceptable for the purpose of this work.

The other important prices for the performed evaluation are the imbalance prices. The differences between these prices and the system marginal price along 2010 are shown in Figure D.6. The difference for up imbalance price is always non positive, while the one for the down imbalance price is always non negative.

It must be remarked that there were some extremely high prices for down imbalances. This phenomenon, although took place only a few hours in the year, has negative effects on the results obtained with this tool, as it will be shown later.

When the imbalance prices are compared to the intraday marginal prices, some

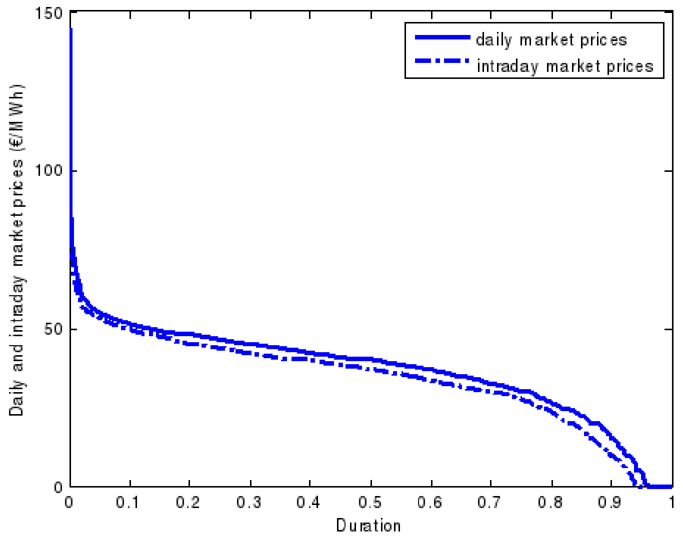


Figure D.4: Daily and intraday market price duration curves.

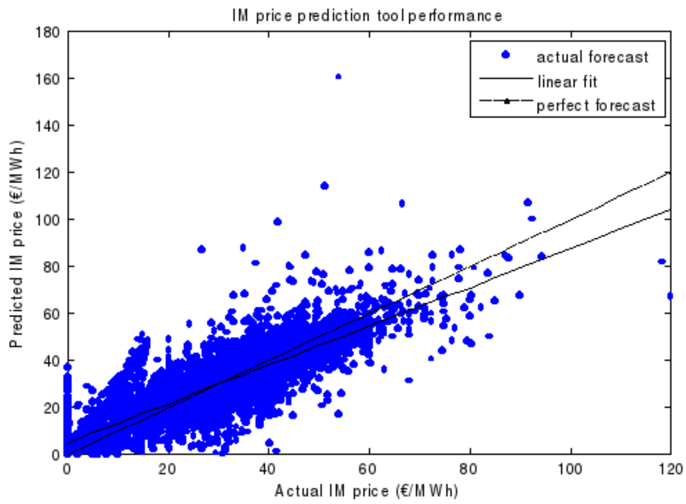
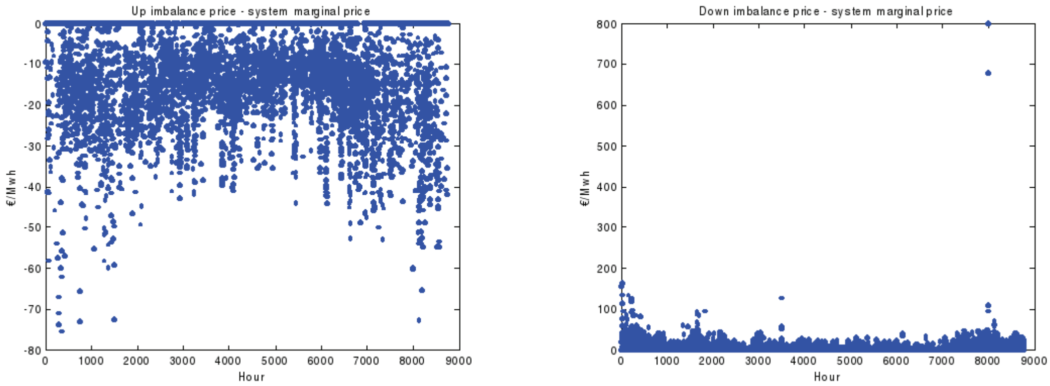


Figure D.5: Intraday marginal (IM) prices in year 2010: predicted vs. actual prices.



(1) Positive imbalances (2) Negative imbalances

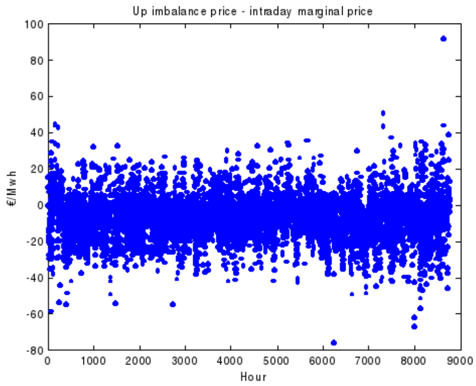
Figure D.6: Difference between imbalance prices and system marginal prices in the Spanish market in 2010.

conclusions may be drawn. Figure D.7 shows the differences between imbalance prices and intraday marginal prices in the Spanish electricity market along 2010. For the moments with a positive difference for up imbalance price (on the left), it would be profitable for a wind power producer being long to incur in an imbalance and be paid at the up imbalance price than adjust the production in the intraday market selling energy. In the same way, a negative value in the difference for down imbalance price (on the right) indicates that it would be profitable for a wind power producer being short to pay for the imbalance than to purchase energy in the intraday market.

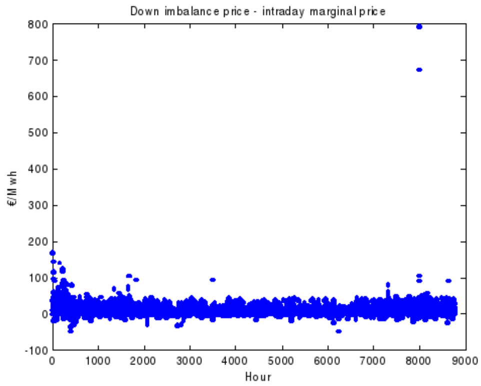
All these considerations are necessary for the evaluation of the results, as it will be shown later, in Subsection D.5.4.

D.5.4 Results of the Trading Tool

The simulation results of the standard (point prediction) strategy and the proposed strategy for the selected wind farms are presented in Table D.5. Benefits of the proposed strategy, vs. the standard one, are also shown, both in € and in %. It may be seen that better results are obtained for all the wind farms selected in the demonstration case. The total benefit of the strategic bidding tool is 321,200 €, which leads to an increase of 1.3% over the standard method revenue for these wind farms. Also it can be observed a great variability in the benefits of each wind



(1) Positive imbalances



(2) Negative imbalances

Figure D.7: Difference between imbalance prices and intraday marginal prices in the Spanish market in 2010.

farm, from 0.1% in the case of wind farm C to 2.8% in the case of wind farm G.

Regarding the power imbalance, the average absolute power error (APE) has been calculated for each wind farm as follows

$$APE = \frac{1}{8760} \sum_{t=1}^{8760} |P_{i,t} - P_{g,t}| \quad \text{(D.10)}$$

In this case, the tool does not minimize this parameter, but on the contrary, absolute power error increases in all the cases, as it can be observed in Figure D.8. This behaviour confirms the idea exposed before that the most accurate prediction of wind power production does not lead to the highest revenues. From Figure D.8, the wind farm G is the most difficult to predict, but it is the one with larger profits (from Table D.5).

If $APE_{proposed}$ is the absolute power error obtained with the proposed method and $APE_{standard}$ is the absolute power error for the standard method, let ΔAPE be the relative difference between both errors (i.e., the absolute power error relative increase):

$$\Delta APE(\%) = \frac{APE_{proposed} - APEstandard}{APE_{standard}} 100 \quad \text{(D.11)}$$

Trying to explain the different benefit observed in each wind farm, that benefit (in %) has been represented vs. the absolute power error relative increase (ΔAPE) obtained with the proposed method. Results are presented in Figure D.9, showing

Wind Farm	Installed capacity (MW)	Proposed method revenue (M€)	Standard method revenue (M€)	Benefit	
				(€)	(%)
A	33	3.57	3.55	20,300	0.6%
B	24	1.54	1.51	33,600	2.2%
C	21	1.68	1.68	2,200	0.1%
D	36	2.65	2.62	30,800	1.2%
E	33	2.34	2.28	60,800	2.7%
F	21	1.65	1.62	28,000	1.7%
G	50	3.38	3.29	92,800	2.8%
H	49	4.56	4.53	30,300	0.7%
I	50	4.16	4.14	22,400	0.5%
Total	317	25.54	25.22	321,200	1.3%

Table D.5: Revenues obtained with proposed and standard methods.

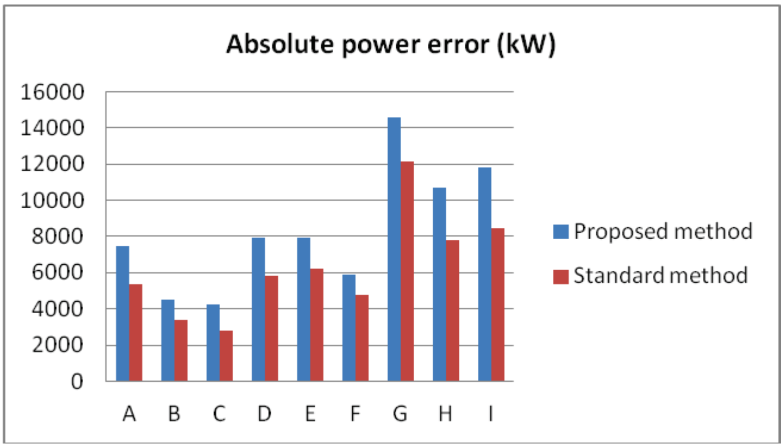


Figure D.8: Absolute power error for each wind farm that the higher relative increase in the absolute power error, the lower benefit for the wind farm producer, i.e., the performance of the proposed method is better when the power errors remain fenced.

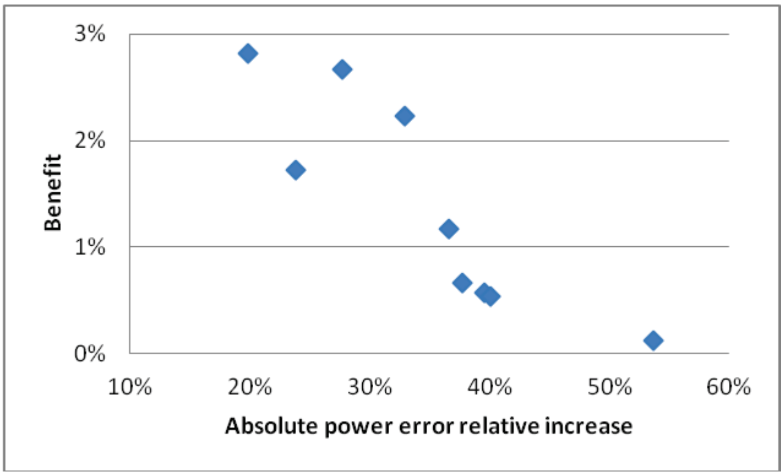


Figure D.9: Benefit vs. absolute power error increase for the proposed method.

Making allowance for the previous deliberation, it would be interesting to examine the reduction in the power error, and thus, the increase in total revenues when the aggregation of wind power is considered. Unfortunately, the bidding decision support tool cannot be used in this case because the uncertainty of the aggregated production forecasts is not available, and neither easily inferred. Then only the deterministic forecasts have been considered and the results are presented in Table D.6. The third column shows the forecast errors (absolute power error) for each individual wind farm and for the aggregation of the nine wind farms in kW. In order to compare these errors, they have been normalized dividing by the installed capacity. The fourth column presents the normalized error in %. The average error of the individual wind farms is 18%, but it diminishes to 9% when the aggregation of the wind farms is considered. Finally the fifth column shows the sum of the individual revenues (25.22 M€) and the revenue obtained with the aggregated forecasts. The combined portfolio benefit is 7.1%, much greater than the proposed bidding strategy for individual wind farms.

Although results are good enough and show the interest of the proposed strategy, several considerations should be taken into account in order to improve them:

- The tool only maximizes the expected value of the total revenue for each

Wind Farm	Installed capacity (MW)	Standard method APE (kW)	Standard method normalized APE (%)	Standard method revenue (M€)
A	33	5,349	16%	25.22
B	24	3,387	14%	
C	21	2,764	13%	
D	36	5,813	16%	
E	33	6,193	19%	
F	21	4,748	23%	
G	50	12,164	24%	
H	49	7,785	16%	
I	50	8,438	17%	
Aggregation	317	29,398	9%	27.01

Table D.6: Standard method individual and aggregated results.

hourly period. In the evaluation period some extremely high down imbalances prices occurred (such as 735.72 €/MWh and 859.13 €/MWh, at hours 17-18 in November 29). The losses at these hours were very high in seven of the nine farms.

- The zero prices in daily and intraday markets affect the performance of the intraday price prediction tool and decrease the overall quality of the forecasts. This tool was designed when zero prices did not occur, but this phenomenon is becoming more frequent, due to the higher penetration of wind farms in the system, and it should be taken into account.

- The portfolio effect is the most valuable for increasing the revenues of wind power producers, so the decision support tool should be used also for the aggregation of a group of wind farms, but the uncertainty of the aggregated production forecasts is needed. With the combination of both, portfolio effect and the use of the trading tool, an even greater improvement of the revenues could be foreseeable.

D.6 Conclusions

Probabilistic tools (wind power forecast, intraday marginal price forecast and imbalance prices estimation) help to reduce economic losses due to imbalance costs. A study has been made for nine wind farms spread in a wide area of the Spanish territory and in accordance to the Spanish market rules. For the examined cases, the revenues were overall increased in a 1.3% but, in some wind farms, benefits have exceeded the 2.5%. This amount is large enough, since, on the one hand the investments needed are very low or null, and on the other hand because in absolute terms (more than 300,000 € a year for nine farms) is attractive enough for wind power producers, especially for big companies.

The proposed method improves the traditional one in all the wind farms considered, leading to higher revenues for the wind power producer but also to a higher energy imbalance. The absolute error between contracted power and production may increase up to 55% with respect to the strategy taken as reference (point predictions). However, in the studied cases this large relative figure is not so high since it refers to wind farms with low prediction errors. It has also been observed that in the cases with higher error increment, the proposed probabilistic strategy yields lower benefits. For all these reasons, it cannot be concluded that the proposed strategy would increase significantly the imbalances in the power system.

A decrease in imbalance losses reduces the need of subsidy for wind energy and makes it more competitive in electricity markets. The objective of reducing the imbalance losses of wind power producers has been fulfilled. This means that if an increase of, say, 1% in the revenues may be achieved in this way, the profitability of the wind farms, and hence the return of the investment, might be achieved with the same reduction in the subsidy. The idea is to encourage wind farm owners to profit as much as possible the possibilities of the electricity markets, reducing what could be regarded as the highest variable cost of the wind farms, namely, the imbalance costs.

As the wind power penetration levels increase, it is expected to have more hours with zero prices in windy days with low demand. This may complicate the prediction/estimation of market prices. Besides, if the proposed probabilistic strategy is widely extended, the effect would be stronger, because of the similarity of the weather prediction tools used by the different companies. This means that intraday marginal prices would be altered, because of the already mentioned lower liquidity of these markets. The strategy would have to be thus modified in order to produce bids with price, i.e., bids that would be accepted only beyond or below a certain price.

Making use of portfolio effect could be also studied. In Spain a bid may be presented for a cluster of farms in order to take advantage of the portfolio effect that decreases the overall prediction error for the whole of the farms, as it has been checked before. In this case, and only with more accurate prediction tools and with a different modelling of the uncertainty, the results could be different. This study would be of great practical interest.

Acknowledgments

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Apéndice E

Efectos de una alta penetración de energías renovables en el sistema eléctrico

E.1 Introducción

En los últimos años se ha experimentado un gran incremento de la presencia de la energías renovables en los sistemas eléctricos. Hasta ahora la energía eólica ha experimentado un considerable aumento de su capacidad instalada, por lo que la mayor parte de los estudios realizados hasta el momento se han centrado en evaluar sus efectos sobre el sistema eléctrico.

El aumento de la penetración de la energía eólica ha estado acompañada de cambios tanto en los mercados eléctricos como en la operación del sistema eléctrico y de las centrales convencionales. Desde el punto de vista de la gestión de la red, uno de los efectos experimentados ha sido el aumento de las congestiones, puesto que la producción de la generación no siempre está cerca de los puntos de consumo, y las redes estaban diseñadas sin tener en cuenta la ubicación de estas fuentes energéticas. En lo que respecta a la programación de la generación, los niveles de las reservas han aumentado debido, por un lado, a la variabilidad de la energía eólica, y por otro, a su parcial predictibilidad que implica en muchos casos una sobre estimación de la reserva necesaria. Además de eso, el resto de las centrales convencionales han cambiado su modo de operación para adaptarse a las características de la producción eólica aumentando el número de puestas en marcha y paradas y la operación a carga parcial. Estas dos últimas características tienen efectos perniciosos en el tiempo de vida de estas centrales y, por tanto, en los costes variables en los que se incurre. Por un lado, se hace un uso más severo de las rampas de producción, y por otro, la operación a carga parcial tiene un rendimiento menor para estas centrales.

En lo que respecta a los precios del mercado, se experimenta por un lado una disminución de los precios[1], puesto que las centrales renovables tienen un coste marginal de producción cero, al tiempo que aumenta su volatilidad; pero por otro lado, se incrementan los costes de provisión de reservas y aumentan los pagos por capacidad.

Por todo lo anterior es necesario realizar estudios para evaluar estos efectos, que aunque han proliferado enormemente en los últimos años, están centrados mayoritariamente en la energía eólica. En Holttinen et al. [35, 36] se presentan los resultados comparativos de estudios de integración de energía eólica en varios países, Irlanda, Reino Unido, Alemania, Dinamarca, Finlandia, Estados Unidos, Portugal, Holanda y España. En este último caso tan sólo se incluyen resultados de estudios de cortocircuitos en la red.

En países con abundante recurso solar, como por ejemplo, en el sur de Europa, se hace necesario estudiar los efectos de sistemas con alta penetración de renovables que no estén basados exclusivamente en los efectos de la energía eólica, sino que además tengan una considerable producción energética procedente de tecnologías fotovoltaica y termoeléctrica. En el caso de esta última tecnología la posibilidad de almacenamiento está haciendo que su implantación haya aumentado considerablemente en los últimos años, por lo que es necesario considerar su existencia y modelar sus características para incluirla en los estudios de planificación de los sistemas eléctricos. Teniendo en cuenta esto, en este trabajo se ha realizado un modelo de la energía solar termoeléctrica que se explicará en detalle en la sección E.2.1.

Existen diversas aproximaciones para evaluar los sistemas eléctricos futuros con alta penetración de renovables.Un enfoque posible puede encontrarse en el estudio realizado por García Casals et al. [37], donde se cuantifica y evalúa técnicamente la

[1] Con respecto a escenarios con los mismos precios de los combustibles y distintas penetraciones de energías renovables.

factibilidad de un sistema eléctrico operado exclusivamente por energías renovables en el sistema peninsular español.

Unas de las variables a tener en cuenta al estudiar los efectos de una alta penetración de renovables en el sistema eléctrico son las decisiones de inversión óptimas para realizar una planificación a largo plazo. El modelo Balmorel (Balmorel [38]) analiza sistemas energéticos y de calefacción[2], evaluando las distintas alternativas de inversión y optimizándolas. En Karlsson & Meibom [39] Balmorel se utiliza para estudiar la ruta a seguir para conseguir que un 70 % del consumo energético del sector transporte sea de origen renovable. En Münster & Meibom [40] se presenta un análisis del uso de basura para la producción de energía en Alemania y los países nórdicos en 2025. Otro ejemplo puede encontrarse en Juul & Meibom [41] donde se estudia la integración de los sistemas eléctrico y de transporte. Los estudios optimizan las inversiones tanto en centrales eléctricas como en vehículos eléctricos en 2030 en Dinamarca y los resultados son ampliados para Alemania, Dinamarca, Finlandia, Noruega y Suecia en Juul & Meibom [42].

Para analizar los efectos en la operación del sistema y en el mercado de un mix de generación futuro se emplea habitualmente un modelo de programación horaria o "unit commitment". Como resultado se establece cuál es el número de unidades que deben estar operativas en cada hora así como la potencia que suministran. Cuando se incluye una unidad en la programación, es necesario ponerla en funcionamiento, sincronizarla con la red y conectarla para que pueda suministrar energía al sistema eléctrico, por tanto esta decisión implica costes económicos. La programación horaria se resuelve mediante un problema de optimización que determina cuáles son las unidades mínimas necesarias que deben estar conectadas para suplir la demanda, puesto que programar unidades adicionales supone un importante coste económico. Para ello, deben tenerse en cuenta las restricciones del problema, tales como la reserva necesaria en el sistema eléctrico, las restricciones térmicas de las unidades (los tiempos mínimos de operación y apagado, rampas, potencia mínima), la coordinación hidro térmica y los combustibles. En resumen, en el problema de programación deben incluirse las características del parque de generación junto con la previsión de la demanda y la producción esperada de energías renovables. Tras la optimización, que habitualmente es horaria, puesto que éste es el periodo temporal considerado en algunos mercados, se obtienen las series de producción de

[2]En los países nórdicos existen mercados de energía térmica.

las distintas tecnologías. En este modelado se supone un mercado de competencia perfecta, es decir, sin considerar que exista poder de mercado.

E.1.1 Objetivos

Los objetivos planteados en este trabajo se detallan a continuación:

- Evaluación de los costes de operación de un mix energético con una alta penetración de energías renovables.
- Análisis de la influencia de una alta proporción de la producción eléctrica de origen renovable en la operación de las centrales no renovables.
- Cuantificación de la reducción de las emisiones de gases de efecto invernadero y evaluación del cumplimiento del protocolo de Kyoto.

Para llevar a cabo estos objetivos se han implementado las siguientes tareas:

- Modelado de las características del sistema eléctrico español, que incluya las características térmicas de sus centrales convencionales y sus restricciones.
- Obtención de la producción horaria de las centrales termoeléctricas a partir de su potencia instalada, capacidad de almacenamiento, localización y radiación prevista, mediante la simulación de su funcionamiento físico.
- Previsión de las series de producción de otras energías renovables en el sistema eléctrico español: biomasa, fotovoltaica, hidráulica (fluyente, embalses), a partir de los datos históricos de producción horaria y de las asunciones de capacidad establecidas en el PANER.
- Generación de escenarios de producción hidráulica deterministas para el mix energético en el año 2020 en España, teniendo en cuenta distintos tipos de años meteorológicos.
- Inclusión en los escenarios de distintas hipótesis de futuros precios de los combustibles y de los derechos de emisión de CO_2.
- Ampliación de la herramienta de unit commitment utilizada, incluyendo un modelo de la energía termoeléctrica para estudiar los efectos de un sistema con alta penetración de energías renovables.

- Análisis de los resultados de los distintos escenarios.

E.1.2 Estudio implementado

Este estudio evalúa los costes de operación de un sistema eléctrico con alta penetración de energías renovables en escenarios futuros. Para ello se ha construido un modelo del sistema eléctrico español.

Las características generales del modelo implementado son:

- Ámbito geográfico. El modelo del sistema eléctrico comprende la región peninsular española.

- Planteamiento del estudio. Problema lineal determinista que evalúa los costes de la generación eléctrica y los precios futuros del mercado diario en un sistema con alta penetración de energías renovables.

- Escenarios futuros. Se definirán distintos escenarios futuros que incluyen datos de la estructura del mix de generación actual y futuro, así como las series de previsiones de demanda y de producción de energías renovables.

En relación con la generación de escenarios futuros se ha tomado como punto de partida el Plan Nacional de Acción de Energías Renovables (PANER) que fue elaborado por el Ministerio de Industria. Este documento contiene las expectativas futuras de producción de energías renovables y establece cuál será la capacidad instalada de estas nuevas tecnologías en el año 2020. Este plan fue elaborado para cumplir con las exigencias de la directiva europea 2009/28/CE (European Commission [100]) que fija como objetivo general de la Unión Europea alcanzar un porcentaje de un 20 % de producción energética bruta procedente de fuentes renovables sobre el consumo final. En él se establecen las capacidades instaladas requeridas para cada tecnología de origen renovable para el cumplimiento de este objetivo, teniendo en cuenta la estructura de generación actual. Además de lo anterior, el plan contempla el diseño de nuevas directivas nacionales en materia energética para fomentar la inversión en tecnologías renovables.

En este estudio se ha partido de los mismos supuestos que el PANER en el diseño de los escenarios y se presentarán los resultados obtenidos bajo distintas hipótesis. Además se ha establecido un escenario adicional que supone el incumplimiento de las previsiones del PANER en cuanto a capacidad instalada, producción renovable y demanda, basándose en las desviaciones existente entre los valores del año 2012 y las predicciones del PANER. Por tanto, se supone que no se cumplirán las previsiones del plan en cuanto a capacidad instalada. De manera análoga, en ese escenario se tiene en cuenta que en los últimos años debido a la crisis económica, la demanda eléctrica ha disminuido y que, por tanto, los escenarios de proyección de demanda establecidos en el PANER distan de la realidad posible. En consecuencia, se ha calculado la proyección de la demanda en función de los datos actuales y de las previsiones de crecimiento del Fondo Monetario Internacional.

Para generar los escenarios se ha planteado que hay distintos parámetros que influirán en los costes futuros del sistema eléctrico. Por un lado, los precios de los combustibles fósiles influyen en el precio marginal del mercado diario. Puesto que el valor futuro de esta variable es tremendamente incierto, se han definido distintos escenarios de acuerdo con las consideraciones de Energy Information Administration [101], definiendo precios bajos, medios y altos en función de las hipótesis formuladas. En relación a las centrales convencionales otra variable a tener en cuenta será la de los distintos precios de emisiones de dióxido de carbono. En este caso, debido a la alta volatilidad de este mercado, es complicado establecer una estimación de los precios futuros. Por ello, se han fijado tres escenarios futuros con valores extremos para evaluar la influencia de esta variable. El último parámetro que se ha tenido en cuenta ha sido la disponibilidad de recurso hidráulico en cada escenario. Puesto que las precipitaciones anuales varían enormemente de un año para otro, es posible que nos encontremos años con abundante recurso y otros con una tremenda escasez. Teniendo en cuenta que esta tecnología permite el almacenamiento, actúa como compensador de la variabilidad de la producción dentro del mix de generación y, por tanto, su disponibilidad o escasez podría influir en la estructura de la generación y en los precios. Este parámetro depende exclusivamente de las condiciones meteorológicas por lo que se han establecido distintos escenarios con bajas, medias y altas precipitaciones basados en los datos históricos disponibles.

La contribución de la producción térmica convencional a la generación eléctrica es una variable a evaluar en este estudio. Para ello se consideran los consumos de combustible, las emisiones de dióxido de carbono y los tiempos de respuesta a la variación de la producción de las centrales (rampas de generación) de las distintas tecnologías. Todos estos parámetros influirán en la disponibilidad de estas centrales para generar energía eléctrica en un determinado momento, y en su modo de operación. En consecuencia el precio de la energía en cada hora dependerá del recurso disponible procedente de fuentes renovables y de la generación térmica convencional.

Puesto que los combustibles de las tecnologías renovables tienen un coste variable cero, se consideran los precios marginales de estas tecnologías iguales a cero. Por tanto, el precio en el mercado diario estará determinado por el coste marginal de la tecnología convencional más cara que esté produciendo en ese momento. Este precio vendrá definido por los resultados de la optimización de la programación horaria.

A la hora de realizar un modelado de un sistema eléctrico con alta penetración de fuentes renovables es posible realizar un análisis determinista o estocástico. Este último se lleva a cabo cuando se pretenden evaluar los efectos de los errores de predicción en los costes del sistema, la provisión de reservas o el modo de operación de las centrales convencionales. Además podrían incluirse estudios de fiabilidad en los que se evalúen los efectos de las paradas forzadas de las centrales en el sistema eléctrico, y la posibilidad de aumentar la ratio de energía no suministrada. Aunque la realización de estos estudios se plantea como un trabajo futuro a desarrollar este apartado se ha limitado a un estudio determinista.

Puesto que se ha estudiado el comportamiento de un productor eólico en el mercado eléctrico, modelándolo en todo momento como "tomador de precios", a ciertas escalas de penetración de energías renovables cabría dudar de la validez de esta hipótesis. Es por ello, que se ha implementado un modelo para evaluar la influencia en el precio del mercado de la presencia de grandes cantidades de energía eólica. Una consecuencia evidente será la disminución del precio del mercado, pero este descenso acarrea también otros efectos como el hecho de que las energías renovables sustituirán a los generadores convencionales, con lo que estos últimos operarán de un modo mucho más flexible, lo que lleva asociado un sobre coste. Este estudio pretende analizar, por un lado, los efectos sobre el precio de la energía, atendiendo a su componente principal, es decir, el precio del mercado diario, y por otro lado, las variaciones en la operación de las centrales convencionales. Adicionalmente, se ha incluido un modelado en detalle de una tecnología emergente en el sistema eléctrico español, como es la termoeléctrica, que se ha incluido en la herramienta de planificación Wilmar. Se deja para un trabajo futuro la ampliación a un estudio estocástico que considere los errores de predicción de la producción de origen renovable e incluya el modelado del mercado intradiario.

En este estudio no se han tenido en cuenta análisis de red ni los efectos de las interconexiones con Francia o Portugal.

E.1.3 Estructura del estudio.

En este trabajo se abordará el problema de la integración de las energías renovables en el sistema eléctrico. Para ello se plantea en primer lugar la formulación del problema de la programación horaria de la generación. Posteriormente se introduce la herramienta seleccionada para resolver el problema, Wilmar. A continuación se presentarán las hipótesis de modelado de las distintas tecnologías, la demanda y las reservas. En el caso de la tecnología termoeléctrica se ha implementado un modelo que simula su funcionamiento físico y proporciona las series de producción futura, mientras que en el resto de los casos las series futuras se han basado en datos históricos. Posteriormente se muestran los resultados obtenidos. El estudio finaliza señalando las conclusiones más relevantes.

E.1.4 Programación de la generación con renovables

La formulación general de un problema de programación horaria puede expresarse con las ecuaciones que se presentan a continuación, siendo la ec. (E.1) la función objetivo y las ecuaciones (E.2) a (E.10) las restricciones. La función objetivo minimiza los costes del sistema eléctrico.

$$\begin{aligned} min\, V_{OBJ} = & \sum_{F_i \in Fuel} \sum_{i \in I^{fuel}} \sum_{t \in T} \sum_{s \in S} \pi_s F_{s,t,i} f_{F_i}^{price} + \sum_{i \in I^{elec}} \sum_{s \in S} \sum_{t \in T} \pi_s O_i P_{i,s,t} \\ & + \sum_{i \in I^{online}} \sum_{s \in S} \sum_{t \in T} \pi_s c_i^{Startup} P_{i,s,t}^{Startup} + \sum_{i \in I^{fuel}} \sum_{t \in T} \sum_{s \in S} \pi_s F_{s,t,i} f_F^{emis} f_{CO_2}^{tax} \\ & + \sum_{r,\bar{r} \in R} \sum_{t \in T} \sum_{s \in S} \pi_s l_{r,\bar{r}}^{trans,cost} P_{r,\bar{r},s,t}^{trans} - \sum_{i \in I^{online}} \sum_{s \in S} \sum_{t \in T} \pi_s Sp_i^{online} P_{i,s,t}^{online} \\ & - \sum_{i \in I^{hydro}} \sum_{s \in S} \sum_{t \in T} \pi_s Sp_i^{hydro} V_{i,s,t}^{hydro} - \sum_{i \in I^{pump}} \sum_{s \in S} \sum_{t \in T} \pi_s Sp_i^{pump} V_{i,s,t}^{pump} \end{aligned} \tag{E.1}$$

$s.a.$

$$\sum_{i \in I_{Elec}} P_{i,t}^{DM} + j_{i,t}^{run-of-river} + j_{i,t}^{biomass} + j_{i,t}^{PV} + P_{r,t}^{Wind} - P_{r,t}^{Windshed} + j_{i,t}^{CSP}$$

$$= \sum_{i \in I^{pump}} W_{i,t}^{DM} + D_{r,t}^{Elec} \tag{E.2}$$

$$P_{i,s,t} \ \leq \ p_i^{Maxprod} \tag{E.3}$$

$$P_{i,s,t} \ \geq \ p_i^{Minprod} \tag{E.4}$$

$$\forall i \in I^{Elec}, \forall s \in S, \forall t \in T$$

$$F_{s,t,i} \ = \ e_i P_{i,s,t}^{online} + f_i P_{i,s,t} \tag{E.5}$$

$$\forall i \in I^{fuel}, \forall s \in S, \forall t \in T$$

$$P_{i,s,t} - P_{i,s,t-1} \leq P_{i,s,t}^{Ramp\_rate} \tag{E.6}$$

$$\forall i \in I^{ramp}, s \in S, t \in T$$

$$V_{i,s,t}^{pump} \leq v_i^{str\_pump,max} \tag{E.7}$$

$$\forall i \in I^{pump}, s \in S, t \in T$$

$$t - t_i^{min\_op} \leq \tau_{op} \leq t - 1 \tag{E.8}$$

$$\forall i \in I^{Elec}, s \in S, \forall t \in [t_i^{min\_op}, ..., T^{opt}]$$

$$t - t_i^{min\_sd} \leq \tau_{sd} \leq t - 1 \tag{E.9}$$

$$\forall i \in I^{Elec}, s \in S, \forall t \in [t_i^{min\_sd}, ..., T^{opt}]$$

$$P_{r,\bar{r},s,t}^{trans} \leq l_{r,\bar{r}}^{trans,max} \tag{E.10}$$

$$\forall r, \bar{r} \in R, \forall t \in T, \forall s \in S$$

Los sumandos de la función objetivo representan los costes de producción del sistema eléctrico. El primer sumando de la función objetivo representa los consumos de combustible durante el periodo de optimización. El segundo corresponde a los gastos debidos a la operación y mantenimiento de las centrales. A continuación se incluyen los costes debidos a las puestas en marcha de las unidades. Después se adiciona la compra de derechos de emisiones de dióxido de carbono. Por último se añaden los costes de la transmisión de energía en las interconexiones entre distintas regiones. Posteriormente es necesario tener en cuenta la capacidad disponible de las unidades en funcionamiento en el periodo de optimización, este término debe restarse pues no es un coste sino energía disponible y tiene un valor asociado. De manera análoga se computa el valor económico que suponen la energía hidráulica embalsada y la energía disponible en los almacenamientos de bombeo.

Las restricciones del modelo representan:

- La ecuación (E.2) representa el equilibrio entre generación y demanda en el mercado diario.
- Ec. (E.3) limita la producción máxima de cada central a su potencia nominal.
- Ec. (E.4) fija el límite de producción mínima para cada unidad. Puesto que no se utilizan variables enteras, se utiliza una variable auxiliar, capacidad online, $P^{online}_{i,s,t}$, que se definirá posteriormente en la sección E.1.5.
- Ec. (E.5) establece los costes de consumo de combustible de cada planta.
- Ec. (E.6) impone las restricciones de rampa, es decir, la potencia máxima que se puede incrementar o disminuir en un periodo de tiempo.
- Ec. (E.7) establece la máxima capacidad de almacenamiento para el bombeo en el sistema.
- Ec. (E.8) fija los mínimos tiempos de operación para las centrales.
- Ec. (E.9) indica el tiempo mínimo durante el que las unidades deben estar apagadas, una vez que se ha decidido su desconexión.
- Ec. (E.10) limita la capacidad de transmisión máxima entre las regiones del modelo.

Los parámetros considerados en el problema de optimización y los símbolos empleados en la formulación están recogidos en la tabla E.1.

Parámetro	Descripción
$c^{Startup}_i$	Costes de encendido de la unidad i.[€/MWh]
$D^{Elec}_{r,t}$	Demanda eléctrica en el periodo t. [MW]
e_i	Parámetro de consumo de combustible de la unidad i.
$f^{tax}_{CO_2}$	Precio de los derechos de emisión de CO_2. [€/tn]
f^{emis}_F	Emisiones de CO_2 al utilizar el combustible F. [tn]

Continua en la siguiente página

Parámetro	Descripción
f_i	Parámetro de consumo de combustible de la unidad i dependiente del rendimiento de la carga cuando está encendida.
$f_{F_i}^{price}$	Precio del combustible F_i. [€/GJ]
$j_{i,t}^{biomass}$	Producción procedente de biomasa en el periodo t. [MW]
$j_{i,t}^{CSP}$	Producción termosolar en el periodo t. [MW]
$j_{i,t}^{inflow}$	Aportaciones horarias de los embalses. [MW]
$j_{i,t}^{run-of-river}$	Producción hidráulica fluyente en el periodo t. [MW]
$j_{i,t}^{PV}$	Producción fotovoltaica en el periodo t. [MW]
$l_{r,\bar{r}}^{trans,cost}$	Costes de transmisión entre dos regiones del modelo. [€/MW]
$l_{r,\bar{r}}^{trans,max}$	Capacidad de transmisión máxima entre regiones. [MW]
$Loss_{carga}$	Pérdidas por almacenamiento en bombeo.
O_i	Costes de operación y mantenimiento. [€/MWh]
$p_i^{Maxprod}$	Potencia eléctrica máxima para la unidad i. [MW]
$p_i^{Minprod}$	Potencia eléctrica mínima para la unidad i. [MW]
$P_i^{Ramp\_rate}$	Rampa de subida o bajada de la unidad i. [MW]
$P_{r,t}^{Wind}$	Potencia eólica en la región r en el periodo t. [MW]
$Sp_{i,s,T}^{pump}$	Precio sombra del agua almacenada al final del periodo. [€/MWh]
$Sp_{i,s,T}^{hydro}$	Precio sombra del contenido del embalse al final del periodo. [€/MWh]
$Sp_{i,s,T}^{online}$	Precio sombra de la unidad i por estar encendida al final del periodo. [€/MW]
$Ramp_{rate}$	Ratio de restricción de rampa en función de la capacidad online.
$t_i^{min_op}$	Tiempo mínimo durante el que la unidad debe estar encendida. [h]
$t_i^{min_sd}$	Tiempo mínimo durante el que la unidad debe estar apagada. [h]
$v_i^{str,max}$	Capacidad máxima de almacenamiento de las unidades de bombeo. [MW]
$v_i^{Hydromax}$	Capacidad máxima de los embalses. [MWh]
$v_i^{Hydromin}$	Capacidad mínima de los embalses. [MWh]
w_i^{MAX}	Capacidad máxima de bombeo. [MWh]
π_s	Probabilidad de ocurrencia del escenario.

Tabla E.1: Parámetros considerados en la optimización

En la tabla E.2 se indican los conjuntos considerados en el problema de optimización, y los índices asociados en la formulación.

Conjunto	Descripción
F, F_i	Combustibles.
i	Unidad.
I^{pump}	Unidades de bombeo.
I^{elec}	Centrales eléctricas
I^{fuel}	Unidades que utilizan combustible (carbón, gas natural, fuel-oil).
I^{online}	Unidades encendidas.
I^{ramp}	Unidades con restricciones de rampa.
r, $\bar{r}$, R	Área o región.
s, S	Escenario.
t, τ, T	Periodo de optimización, T describe el último periodo de optimización de un escenario.

Tabla E.2: Conjuntos considerados en la optimización

Como resultado del problema de optimización se obtienen los valores de un conjunto de variables de decisión que están resumidas en la tabla E.3.

Variable	Descripción
$F_{s,t,i}$	Uso del combustible en escenario s en el instante t para la unidad i. [MW]
$P_{i,s,t}$	Producción de la unidad i en el periodo de optimización t. [MW]
$P_{i,t}^{DM}$	Energía casada en el mercado diario para la unidad i en el periodo de optimización t. [MW]
$P_{i,s,t}^{online}$	Capacidad online de la unidad i. [MW]
$P_{i,s,t}^{Startup}$	Capacidad de encendido de la unidad i en el periodo de optimización t. [MW]
$P_{r,\bar{r},s,t}^{trans}$	Potencia transmitida entre dos regiones del modelo. [MW]
$P_{r,t}^{Windshed}$	Energía eólica vertida. [MW]
$V_{i\in I^{pump},s,t}^{pump}$	Contenido del almacenamiento al final del periodo de optimización. [MWh]
$V_{i\in I^{hydro},s,t}^{hydro}$	Contenido del embalse al final del periodo de optimización. [MWh]
$W_{i,s,t}$	Energía almacenada para bombeo en el periodo t. [MW]

Tabla E.3: Variables de decisión de la optimización

E.1.5 Herramienta empleada: Wilmar Planning Tool

Existen distintas herramientas para implementar un modelo de "unit commitment". En este caso se ha utilizado la herramienta de planificación Wilmar, por sus numerosas funcionalidades para hacer este tipo de análisis, desarrollada en el ámbito del proyecto de investigación Wilmar (Wind Power Integration in Liberalised Electricity Markets WILMAR [102]) que fue financiado por el quinto programa marco de la Comisión Europea. El proyecto comenzó en noviembre de 2002 y duró 36 meses. La tarea principal del proyecto era analizar la integración de la energía eólica en un sistema eléctrico liberalizado de gran magnitud que cubría las áreas de Dinamarca, Finlandia, Alemania, Noruega y Suecia.

La herramienta de planificación Wilmar fue programada en GAMS (General Algebraic Modelling System). En la primera fase de desarrollo la herramienta realizaba un unit commitment estocástico lineal. Está compuesta por dos módulos:

- Modelo de un mercado de competencia perfecta, JMM (Joint Market Model), explicado en detalle en Meibom et al. [43] . En esta parte se realiza la casación de la energía generada con la demanda simulando un mercado perfecto, es decir, sin considerar que exista poder de mercado. Para ello las energías son casadas en función de sus costes marginales siguiendo el orden de mérito. Por tanto, se minimizan los costes del sistema eléctrico. Además se implementa el modelado de cinco mercados. Uno diario y otro intradiario para la energía producida. Uno diario para la reserva de respuesta automática (primaria) y otro intradiario para las reservas con un tiempo de activación superior a 5 minutos (secundaria). Por último se incluye un mercado de energía térmica. Los valores marginales que se deducen de las ecuaciones de estos mercados proporcionan el precio marginal o de casación de cada uno de ellos.

- Además se incluye un módulo de generación de escenarios de predicciones estocásticas, STT (Scenario Tree Tool). Este módulo proporciona predicciones para la producción eólica, demanda y reservas. Las series son proporcionadas por un módulo ARMA (Autoregressive-moving-average model) que describe el comportamiento de procesos estacionales estocásticos. Puede encontrarse una explicación en profundidad de su funcionamiento en Barth et al. [44].

Se ha empleado esta herramienta para analizar los países nórdicos y Alemania. En Barth et al. [46] se explica en detalle su funcionamiento y se presentan las ecuaciones del problema de optimización y su estructura. Se presentan resultados de precios y estructura de la producción en Alemania, Dinamarca, Finlandia y Suecia para 3 escenarios, la capacidad instalada real en el año 2010, y escenarios con un 10 % y 20 % de producción eólica respecto a la demanda total.

En Meibom et al. [47] se describe el modelado de los mercados de reservas y se estudian los costes de los sistemas a distintos niveles de penetración de energía eólica, usando los mismos escenarios que en el estudio anterior, niveles de 2010, 10 % y 20 % de producción eólica. Se concluye que al aumentar la penetración eólica disminuyen los costes de operación totales, pero aumentan los de las centrales convencionales, puesto que aumenta su operación a carga parcial y el número de puestas en marcha, y en consecuencia, los costes de operación.

En Meibom et al. [48] se presentan los resultados de un estudio que minimiza el valor esperado de los costes de operación en Alemania y los países nórdicos en 2010. Se implementa además un modelo estocástico para la producción eólica y para la reserva secundaria (tiempos de actuación mayores que 5 minutos). Se dividen los costes de integración en dos, estudiando los que son debidos a la parcial predictibilidad y los ocasionados por la variabilidad. Para ello se define otra hipotética tecnología que sustituye a la energía eólica pero con una producción constante. Para calcular estos costes comparan los resultados de tres modelos, uno estocástico, considerando la producción eólica y los errores de predicción; otro determinista, suponiendo una producción eólica variable pero sin errores de predicción en donde se establece un conocimiento perfecto de la producción; y por último, un modelo determinista sin variabilidad, de manera que se supone una producción constante y no se consideran errores de predicción. A partir de estas implementaciones se estudian los costes de la parcial predictibilidad y de variabilidad de la energía eólica, mediante la comparación de los resultados obtenidos. Se tienen en consideración distintas regiones así como sus interconexiones. Se concluye que los costes de integración son menores en sistemas dominados por hidráulica flexible y que aumentan en los países con producción eólica constante con países vecinos con altas capacidades de energía eólica.

En Brand et al. [49] se presenta en detalle el funcionamiento del módulo ARMA para las predicciones de la producción eólica, demanda y reservas. Se presentan resultados para semanas tipo en distintas regiones de Alemania en el año 2020, teniendo en cuenta las capacidades de transmisión entre las regiones. En el estudio se evalúan los precios del mercado, la composición de la generación y los costes del sistema. Los costes de operación se calculan con y sin energía eólica, y además se incrementa la capacidad de transmisión entre las regiones.

Además la herramienta Wilmar ha sido posteriormente empleada para analizar la integración de renovables en un sistema insular, Irlanda. En este caso se implementó un modelo de unit commitment lineal entero mixto estocástico. Son ejemplo de ello las publicaciones que siguen.

En Troy et al. [50] se modelan la demanda, el viento y la demanda de reserva primaria con el STT. Se evalúa cómo influye la inclusión de los costes de encendido en los resultados del unit commitment. Además se realiza un análisis de sensibilidad de la influencia de las interconexiones y el bombeo. En el estudio se evalúa el número de conexiones de las unidades, el factor de capacidad, el factor de utilización, las horas en las que se incurre en rampas severas[3] (sin incluir en estos casos ni las puestas en marcha ni las paradas de las unidades) y las horas de funcionamiento para centrales de carbón y ciclo combinado tipo considerando distintos escenarios de capacidad eólica instalada.

En Gubina et al. [51] se describe un modelo implementado en el operador del sistema irlandés, República de Irlanda e Irlanda del norte, para calcular las reservas con predicciones estocásticas de viento y demanda que incluye las paradas forzadas de las centrales. El modelo incluye un modelado de mercados diarios e intradiarios y optimiza la provisión de las reservas.

En el modelo de Meibom et al. [52] se estudian cinco escenarios con distintos niveles de penetración eólica y diversa composición de las carteras de centrales convencionales. El modelo incluye una planificación recursiva que tiene en cuenta la actualización de las predicciones así como las paradas forzadas de las centrales. Se han estudiado los impactos operacionales de altas penetraciones de energías renovables, incluyendo en los resultados análisis de fiabilidad, previsión de las reservas y estructura de la generación en cada escenario. Estos resultados están ampliados en el estudio "All Island Grid Study" (Meibom et al. [53]).

Siguiendo la línea presentada en este estudio se han realizado trabajos como el

[3]Definida en este artículo como un cambio en la potencia de salida de más de la mitad de la diferencia entre la potencia mínima y máxima de la unidad en una hora.

desarrollado por Tuohy et al. [54, 55] en el que se presentan las ventajas de realizar un "unit commitment" estocástico frente a uno determinista. También se evalúa el impacto de modelar la incertidumbre con distintas escalas temporales, es decir, actualizando las predicciones más a menudo. Se aplica al mix energético en Irlanda en 2020, en concreto al escenario P5 del estudio "All Island Grid Study" (Meibom et al. [53]). Las conclusiones del trabajo señalan las diferencias en los resultados de la programación horaria al aplicar una aproximación estocástica frente a una determinista, y las comparan con el caso en el que se aplicase una predicción perfecta de la producción eólica y la demanda. Como conclusiones del estudio se afirma que las centrales de punta y las de gas con orden de mérito media se incluyen en la programación con más frecuencia en el caso estocástico que en el que se considera predicción perfecta. El número de arranques aumenta cuando se aplica un método estocástico con respecto a los casos en los que se emplean predicciones perfectas, incrementándose para las centrales de punta y de costes medios.

Estructura de la herramienta de planificación Wilmar

La herramienta Wilmar está compuesta por varios módulos: STT y JMM, y por distintas bases de datos que contienen la información correspondiente a las variables del sistema eléctrico necesarias para obtener los resultados de la programación horaria.

Estas bases de datos están descritas en detalle en Kiviluoma & Meibom [45]:

- Input database (Input DB). Contiene todos los datos de entrada necesarios para el JMM. Esta base de datos genera los archivos de entrada del JMM. Incluye datos del parque de generación convencional, series de generación renovables, capacidad instalada, interconexiones, provisión de reservas, ámbito geográfico del modelo, externalidades consideradas, precios de combustibles, entre otras.

- Output database (Output DB). Tras realizar la optimización en el JMM los resultados son cargados en esta base de datos que generará distintas tablas para analizar los resultados de producción, valores marginales de las variables, precios de los mercados, violación de las restricciones del modelo, provisión de las reservas y contenido de los embalses en cada hora, entre otras.

En resumen, el funcionamiento de la herramienta Wilmar comienza con la generación de los escenarios de predicciones en el módulo del STT. Estas series generadas por el STT se incluirán en la Input DB. Además de estos datos, se incluirán las características del sistema eléctrico, las series de producción renovable e históricas de producción hidráulica; se definirá el intervalo temporal de la simulación, así como el ámbito geográfico del modelo. Una vez que el modelo del sistema eléctrico esté completamente definido, la Input DB generará los ficheros de entrada para la simulación en GAMS. Tras eso, se procederá a ejecutar el módulo del JMM que proporcionará los resultados. Posteriormente, se importarán los archivos de salida del JMM en la Output DB donde se procederá a analizar los resultados de la simulación.

Implementación de la programación horaria en Wilmar

Para determinar la programación horaria del problema considerado se ha empleado la función objetivo planteada en la ecuación (E.1). En esta ecuación se ha efectuado una simplificación puesto que tan sólo se ha considerado el sistema peninsular español, que se ha modelado como una región única, y, por tanto, no se han tenido en cuenta los costes y restricciones de transmisión entre distintas regiones, definidas en la ecuación (E.10). En el problema no se han considerado las paradas programadas ni forzadas de las centrales.

La función objetivo minimiza los costes del sistema eléctrico. Dentro de esta función se han incluido además algunas variables de holgura y de las que se hará uso en el caso de que el sistema no sea factible. Estas variables sirven, por ejemplo, para detectar cuáles serían los problemas que debería resolver el parque de generación. En el caso de las rampas, se añade una variable de holgura V^{ramp}, que nos permitiría cuantificar la necesidad de ampliar la capacidad de aumento o disminución de potencia para una planta en el caso de que fuese necesario. Por tanto, su uso nos indicaría la necesidad de unidades más flexibles en el parque de generación. Estas variables de holgura se añaden a las restricciones de manera que ante un problema infactible, obtenemos una factibilidad artificial al incurrir en su uso. Por otro lado, se añaden estas variables a la función objetivo multiplicadas por una penalización muy elevada (300.000€) para que no se haga uso de ellas a no ser que sea imprescindible. Estas variables de holgura se utilizan en las ecuaciones del mercado diario, intradiario, reservas, rampas y tiempos mínimos de operación.

Otra de las simplificaciones que se han llevado a cabo en la resolución del problema ha sido la consideración de un único escenario de producción de energía renovable. Es decir, no se han tenido en cuenta los errores de predicción, y por tanto, nos encontramos ante un problema en el que suponemos un conocimiento perfecto de la producción de antemano. Esta aproximación implicará una estimación a la baja de los costes de las reservas del sistema puesto que la incertidumbre en la producción futura hace necesario aumentar la energía de la reserva ante la posibilidad de que existan errores en la predicción. No obstante, se tendrán en cuenta los costes por el cambio en el modo de operación de las centrales convencionales, que funcionarán más frecuentemente a carga parcial, y que experimentarán un mayor número de apagados y encendidos, con lo que se evaluarán los efectos de la variabilidad de la energía eólica en un escenario con alta penetración. En Tuohy et al. [54] se realizó un análisis de la diferencia en los costes de operación entre un sistema estocástico y otro con predicción perfecta, y se concluyó que en el unit commitment estocástico los costes son entre un 1,5 y 0,8 % superiores a los del caso con predicción perfecta. Por tanto, los resultados obtenidos supondrán un límite inferior de los costes del sistema.

Además de la función objetivo deben plantearse las ecuaciones correspondientes a los distintos mercados. En el caso que nos ocupa tan sólo se ha tenido en cuenta el mercado diario, puesto que no se ha trabajado con predicciones, y por tanto, no están consideradas las actualizaciones de la programación en los mercados intradiarios. La ecuación (E.2) representa la casación del mercado diario. En ella debe cumplirse el equilibrio entre la demanda y la energía generada, y, por tanto, las unidades producirán en función de su orden de mérito, es decir, en primer lugar serán casadas las que menores costes marginales tengan. Como resultado del problema de optimización se proporcionará la energía suministrada por cada unidad. Además el valor marginal del resultado de esta ecuación indica los precios de casación del mercado diario.

Puesto que la cantidad de energía eólica casada en el mercado diario es una variable de decisión, existen situaciones en las que por restricciones térmicas de funcionamiento de las centrales convencionales, entre otras causas, parte de la energía disponible no podrá ser integrada en la red. Esta energía no utilizada se denomina energía eólica vertida, y está formulada en la ecuación (E.11), donde se limita que su valor máximo no puede ser superior a la producción eólica disponible.

$$P_{r,t}^{Windshed} \leq P_{r,t}^{Wind} \qquad \text{(E.11)}$$
$$\forall r \in R, \forall t \in T$$

El modelo utilizado en este caso es lineal y no entero. Es decir, no se considera el estado de las unidades, conectadas o desconectadas, como una variable del problema. Para simular su estado se hace uso de una variable adicional, la capacidad online, $P_{i,s,t}^{online}$ que es empleada para calcular los costes de puesta en marcha, las restricciones de potencia mínima, la potencia máxima y los mínimos tiempos de operación y desconexión en un modelo de programación lineal. Se ha optado por esta aproximación por la dificultad de hacer factible un modelo a escala nacional.

Por tanto hay que definir la capacidad de arranque en la ecuación (E.12).

$$P_{i,s,t}^{Startup} \geq P_{i,s,t}^{online} - P_{i,s,t-1}^{online} \qquad \text{(E.12)}$$
$$\forall i \in I^{online}, \forall s \in S, \forall t \in T$$

Las restricciones de rampa quedarían en función de la capacidad online en la ecuación (E.13).

$$P_{i,s,t} - P_{i,s,t-1} \leq P_{i,s,t}^{online} Ramp_{rate} \qquad \text{(E.13)}$$
$$\forall i \in I^{ramp}, s \in S, t \in T$$

Además, es necesario definir las ecuaciones hidráulicas del modelo, en el que se consideran todas las centrales hidráulicas de manera agregada, considerando por separado las centrales fluyentes y no fluyentes a la hora de realizar dicha agregación. En el caso de las centrales no fluyentes se establece la ecuación (E.14) donde se limita la capacidad hidráulica máxima.

$$V_{i,s,t}^{hydro} \leq \sum_i v_i^{Hydromax} \qquad \text{(E.14)}$$
$$\forall i \in I^{Hydro}, s \in S, t \in T$$

De manera análoga en la ecuación (E.15) se establece el nivel mínimo de los embalses.

$$V_{i,s,t}^{hydro} \geq \sum_i v_i^{Hydromin} \qquad \text{(E.15)}$$
$$\forall i \in I^{Hydro}, s \in S, t \in T$$

La energía almacenada en los embalses en una hora se calcula en la ecuación (E.16) en función del nivel de embalsado en la hora anterior, y la producción y las aportaciones, $j_{i,t}^{inflow}$, en esa hora.

$$
\begin{aligned}
V_{i,s,t}^{hydro} =& V_{i,s,t-1}^{hydro} - P_{i,s,t} + j_{i,t}^{inflow} \\
& \forall i \in I^{Hydro}, s \in S, t \in T
\end{aligned}
\tag{E.16}
$$

Adicionalmente las producciones hidráulicas deben ser menores que la capacidad instalada, incluyendo las centrales fluyentes y no fluyentes, como se establece en la ecuación (E.17).

$$
\begin{aligned}
\sum_{i \in I^{hydro}} P_{i,s,t} + j_{i,t}^{run-of-river} \leq \sum_{i \in I^{hydro}} p_i^{maxprod} + \sum_{i \in I^{run-of-river}} p_i^{maxprod} \\
\forall i \in I^{hydro}, i \in I^{fluyente}, s \in S, t \in T
\end{aligned}
\tag{E.17}
$$

Por otro lado, deben definirse las ecuaciones del almacenamiento eléctrico, que en el sistema español se limitan a centrales de bombeo. En primer lugar se define la ecuación dinámica del almacenamiento, ecuación (E.18), que incluye las pérdidas por almacenamiento.

$$
\begin{aligned}
V_{i,s,t}^{pump} = \sum_{s} V_{i,s,t-1}^{pump} + Loss_{carga} W_{i,s,t} - P_{i,s,t} \\
\forall i \in I^{pump}, s \in S, t \in T
\end{aligned}
\tag{E.18}
$$

En la ecuación (E.19) se limita la capacidad máxima del proceso de carga del bombeo.

$$
\begin{aligned}
W_{i,s,t} \leq w_i^{MAX} \\
\forall i \in I^{pump}, s \in S, t \in T
\end{aligned}
\tag{E.19}
$$

La ecuación (E.20) limita la capacidad máxima del almacenamiento dedicado a bombeo.

$$
\begin{aligned}
V_{i,s,t}^{pump} \leq & v_i^{str,max} \\
& \forall i \in I^{pump}, s \in S, t \in T
\end{aligned}
\tag{E.20}
$$

Los tiempos mínimos de operación de las unidades se definen en función de la capacidad online en la ecuación (E.21).

$$P_{i,s,t-1}^{online} - P_{i,s,t}^{online} \leq P_{i,s,\tau}^{online} \tag{E.21}$$
$$\forall \tau \ s.a.$$
$$t - t_i^{min\_op} \leq \tau \leq t-1, \forall i \in I^{Elec}, s \in S$$
$$\forall t \in [t_i^{min\_op}, ..., T^{opt\_period}]$$

Los tiempos mínimos de parada de las unidades se fijan en la ecuación (E.22) en función de la capacidad online.

$$P_{i,s,t-1}^{online} - P_{i,s,t}^{online} \leq P_{i,s,\tau}^{online} - P_{i,s,t-1}^{online} \tag{E.22}$$
$$\forall \tau \ s.a.$$
$$t - t_i^{min\_op} \leq \tau \leq t-1,$$
$$\forall i \in I^{Elec}, s \in S, \forall t \in [t_i^{min\_op}, ..., T^{opt\_period}]$$

E.2 Modelado de las energías renovables

En esta sección se describen los distintos modelos empleados para estimar la producción de energías renovables en los casos de estudio.

En el caso de la termoeléctrica se ha desarrollado un modelado del funcionamiento físico para obtener sus series horarias de producción a partir de los datos de radiaciones y de las instalaciones, potencia instalada, área de captación solar y capacidad del almacenamiento.

En las otras tecnologías renovables se han determinado las series de producción a partir de datos históricos. En todos los casos se han obtenido series normalizadas que conservan la variabilidad característica de cada una de ellas. Posteriormente, en función del escenario simulado, se multiplicarán estos valores por la producción anual estimada.

E.2.1 Modelado de la tecnología solar termoeléctrica

Introducción

En esta sección se describe el modelo desarrollado para la tecnología solar termoeléctrica. En la literatura pueden encontrarse distintos modelos para este tipo de tecnología. Montes et al. [56] realiza una optimización económica del múltiplo solar de plantas termoeléctricas sin usar hibridación ni almacenamiento térmico.

La tecnología termoeléctrica o energía solar de concentración (CSP, por sus siglas en inglés, Concentrated Solar Power) usa lentes y espejos para concentrar la energía de la radiación solar y, posteriormente, utilizar el calor producido para turbinar un fluido de trabajo y generar energía eléctrica.

En las centrales de producción de energía eléctrica se utilizan tecnologías de alta y media temperatura, en función de las temperaturas alcanzadas por el fluido caloportador. Actualmente, existen distintos tipos de tecnologías de alta temperatura que se diferencian en el tipo de óptica empleada, es decir, el tipo de lentes, y en el fluido caloportador empleado. Podemos clasificarlas en:

- Canales cilindro parabólicos. Está compuesta por colectores parabólicos que reflejan la luz dirigiéndola a concentradores situados en la línea focal de los espejos. Estos receptores están rellenos de un fluido de trabajo (habitualmente sales fundidas), que puede ser calentado hasta 500ºC. Los colectores tienen un sistema de seguimiento solar, de manera que se mueven siguiendo la radiación solar. Actualmente, es la tecnología más empleada.

- Reflectores lineales Fresnel. Consta de lentes Fresnel, que dirigen el calor hacia una tubería que está situada en el centro. La tubería contiene aceite, que será empleado para producir vapor. Después, el vapor obtenido generará electricidad, a través de una turbina.

- Discos parabólicos con motor Stirling. Está compuesto por colectores parabólicos que calientan un fluido, que posteriormente alimentará un motor Stirling. Esta tecnología alcanza los valores de rendimiento más altos para CSP.

- Centrales de torre con helióstatos. Consta de hileras de helióstatos que dirigen la luz reflejada hacia una torre. Dentro de ésta, hay un fluido de trabajo, generalmente agua o sales minerales, que será calentado hasta 500 - 1.000 ºC. Este fluido puede ser utilizado, o bien, para alimentar un generador, o bien, para calentar un sistema de almacenamiento térmico.

Para desarrollar el modelo, en este trabajo se han considerado las características físicas de la tecnología **cilindro parabólica**, puesto que es la más extendida en el sistema eléctrico español. Aunque las otras tecnologías mencionadas también son utilizadas, su baja implantación no justifica su modelado en detalle, por lo que se ha desarrollado un modelo cilindro parabólico simplificado, teniendo en cuenta algunas aproximaciones para obtener la energía producida por esta tecnología en el año de estudio.

Para la obtención de las series de producción se ha tomado como base el modelo físico y de operación de la planta desarrollado por Wagner & Gilman [57].

El objetivo del modelo es diseñar una representación aproximada de la tecnología termoeléctrica que, a partir de las radiaciones solares, ubicación de las plantas, potencia instalada y la capacidad de almacenamiento, proporcione las series horarias de energía producida y la energía disponible en el almacenamiento. Estos datos serán posteriormente integrados en Wilmar para realizar la programación horaria de la generación.

Para explicar el método empleado, la planta termoeléctrica ha sido dividida en distintas partes que se detallan a continuación.

Campo solar. Está compuesto por una serie de colectores solares ensamblados que recogen la radiación solar y la reflejan, con el objeto de concentrarla en los receptores que contienen el fluido caloportador. Por tanto, el campo solar convierte la energía solar[4] en térmica.

El modelado termodinámico a través de ecuaciones diferenciales de transferencia de calor queda fuera del alcance de este trabajo. En su lugar, se han calculado los rendimientos de cada una de las partes del modelo con el objeto de hacerlo más sencillo y manejable, puesto que esta aproximación es suficiente para el objetivo de simular las series de producción de la tecnología CSP. Los parámetros de rendimiento en la conversión de energía, así como el dimensionado, que se explicarán en el siguiente apartado, han sido obtenidos del modelo físico de NREL [60], usando como base los resultados de las simulaciones de una planta de 50 MWe ubicada en Andalucía. Por tanto, en lugar de considerar las ecuaciones de flujo másico, se han empleado los resultados de las simulaciones de este modelo, deduciendo el rendimiento de la conversión de energía solar en térmica a partir de ellos.

[4] Los colectores recogen sólo la irradiancia normal directa.

Ensamblaje de los colectores y óptica. El colector es el dispositivo del campo solar que se encarga de reflejar la radiación solar y dirigirla al receptor. Para determinar el flujo solar en el receptor, será necesario tener en cuenta las pérdidas ópticas constantes y variables.

La radiación total recibida por el campo solar [W] puede ser determinada mediante la fórmula:

$$Q_{SF} = DNI\, A_{SF}\, cos(\theta) \tag{E.23}$$

donde DNI es la irradiancia directa normal (W/m^2) recibida; A_{SF} es el área equivalente de apertura de los colectores, es decir, el área total de reflexión; y θ es el ángulo de incidencia, o el ángulo formado entre la normal al plano de apertura y la radiación solar.

El ángulo de incidencia depende de la posición solar y del seguimiento del sol de los colectores. Generalmente, los colectores hacen un seguimiento de un sólo eje. Lo más habitual es que su eje esté orientado en dirección N-S, con seguimiento E-W. La ventaja de este seguimiento es que se reducen los efectos de las sombras en los casos en los que se emplee más de un colector (Kalogirou [58]).

Antes de determinar el ángulo de incidencia, deben definirse algunos parámetros geométricos solares. En primer lugar debe determinarse la hora solar t_s en función de la hora h, definida por:

$$t_s = h + \frac{desvio_{long}}{15} + \frac{EOT}{60}, \tag{E.24}$$

donde $desvio_{long}$ representa el desvío existente entre la longitud estándar utilizada para fijar la hora, y la longitud real de la ubicación; y EOT es la ecuación del tiempo. Podemos definirlas como:

$$\begin{aligned} EOT &= 9{,}2\,[0{,}000075 + 0{,}001868\, cos(B) - 0{,}032077\, sen(B) \\ &\quad -0{,}014615\, cos(2B) - 0{,}04089\, sen(2B)] && \text{(E.25)} \\ desvio_{long} &= -15 - long && \text{(E.26)} \\ B &= (dia - 1)\frac{360}{365}, && \text{(E.27)} \end{aligned}$$

donde $long$ es la longitud de la ubicación.

La hora solar debe convertirse en un ángulo horario (ω_h):

$$\omega_h = (t_s - 12)15; \tag{E.28}$$

El ángulo de declinación, δ, debido al efecto de la inclinación del eje de la Tierra, puede determinarse a partir de:

$$\delta = 23{,}45\, sen\Big(360\, \frac{284 + dia}{365}\Big) \tag{E.29}$$

Finalmente, es necesario definir el azimut solar,γ_s , y la elevación solar, θ_e, que dependen de la latitud de la ubicación, *latit*:

$$\theta_e = sen^{-1}\big[sen(\delta)\, sen(latit) + cos(latit)\, cos(\delta)\, cos(\omega_h)\big] \tag{E.30}$$

$$\theta_z = 90 - \theta_e \tag{E.31}$$

$$\gamma_s = signo(\omega_h)\, \Big|cos^{-1}\Big(\frac{cos(\theta_z)\, sen(latit) - sen(\delta)}{sen(\theta_z)\, cos(latit)}\Big)\Big| \tag{E.32}$$

Además hay que tener en cuenta el ángulo de seguimiento del colector, que tendrá a su vez un ángulo de azimut, γ_{col}, y un ángulo de inclinación, θ_{col}, de manera que la expresión de $cos(\theta)$ en cada hora se determina en la ecuación:

$$cos(\theta) = \sqrt{1 - [cos(\theta_e - \theta_{col}) - cos(\theta_{col})\, cos(\theta_e)(1 - cos(\gamma_s - \gamma_{col}))]^2} \tag{E.33}$$

En este caso, como se ha supuesto orientación del eje N-S, y seguimiento E-W, los ángulos del colector debidos al seguimiento serán, θ_{col}=0º y γ_{col}=0º.

Pérdidas en el colector. Una vez que se ha determinado la energía solar recibida por los colectores teniendo en cuenta los ángulos solares, es necesario calcular la energía efectiva que el colector transmite al receptor. Para ello hay que tener en cuenta las pérdidas térmicas que tienen lugar en el campo solar, y que se enumeran a continuación:

- **Desenfoque del colector.** Es posible que en determinados momentos la energía térmica producida por el campo solar exceda a la que puede ser absorbida por el ciclo de generación y la que puede almacenarse. Para evitar el sobrecalentamiento del fluido caloportador, y evitar una situación peligrosa, los colectores son desenfocados.

- **Protección contra heladas.** El fluido caloportador no puede alcanzar una temperatura límite inferior. Para evitar esto, en aquellos casos en los que se alcanza una temperatura mínima se empleará una caldera auxiliar para calentar el fluido.

- **Efectos transitorios.** La presencia de nubes y los cambios en la temperatura exterior hace que los sistemas termoeléctricos estén sujetos a fluctuaciones en la energía recibida. Puesto que el tiempo de simulación considerado es muy alto, una hora, deben considerarse estas pérdidas descontando una energía de transición.

- **Pérdidas ópticas.** Implican las pérdidas debidas al seguimiento, defectos en la geometría, suciedad del colector, sombras del colector adyacente durante el amanecer y el atardecer, entre otras.

Receptores. El receptor puede ser modelado mediante un modelo de transferencia de calor. En este caso, por simplicidad, tan sólo se ha tenido en cuenta el rendimiento de la conversión de energía del campo solar.

Calentamiento del campo solar. Cuando comienza a salir el sol, parte de la energía recibida ha de ser empleada en el calentamiento del fluido caloportador. Debe tenerse en cuenta que antes de ese momento el fluido no ha recibido energía solar durante varias horas, por lo que es necesaria una energía adicional para que el fluido llegue a la temperatura de trabajo. Esta energía dependerá tanto de la temperatura externa durante la noche como del número de horas nocturnas. Puesto que este cálculo no es trivial se ha realizado una simplificación para obtener la energía de calentamiento del campo solar a partir del modelo experimental, deduciéndola de la cantidad de energía recibida por el campo solar a lo largo de todo el día aplicando una modelización no lineal que puede encontrarse explicada en Usaola [59].

Modelo de canalizaciones. Las pérdidas más elevadas en una central termoeléctrica son las debidas al bombeo del fluido caloportador.

Por tanto la energía térmica disponible en el fluido caloportador tendrá en cuenta las pérdidas y el calentamiento del campo solar y puede formularse:

$$Q_{HTF} = DNI\ A_{SF}\ cos(\theta)\ \eta_{col} - Q_{warm\_sf} \tag{E.34}$$

donde η_{col} es el rendimiento de captación de energía térmica del colector, que incluye tanto las pérdidas ópticas como otras y Q_{warm_sf} es la energía necesaria para el calentamiento del campo solar.

Ciclo de generación. En el módulo del ciclo de generación la energía térmica es convertida en energía mecánica o eléctrica. Este módulo contiene todo el equipamiento necesario para esta tarea.

En las instalaciones a gran escala, se utiliza un ciclo de vapor Rankine para la generación de electricidad. Los ciclos Rankine están ampliamente utilizados para sistemas de generación a gran escala en centrales nucleares, de biomasa o que emplean combustibles fósiles. Mientras estas centrales trabajan en un estrecho margen respecto al punto de diseño, las centrales termoeléctricas suelen hacerlo en condiciones de operación muy variadas, puesto que dependen de la disponibilidad del recurso solar, de la capacidad del almacenamiento y de las condiciones ambientales, lo que hace que la energía térmica disponible sea muy variable.

Por todo lo anterior, el rendimiento global del ciclo de generación no es un parámetro constante y depende de las condiciones de funcionamiento, de tal manera que una fuente de calor a mayor temperatura o un sumidero más frío pueden incrementar el rendimiento del ciclo Rankine. En consecuencia, puesto que el aire del exterior es utilizado en el sistema de refrigeración, el rendimiento del ciclo dependerá de esta temperatura.

Modos de operación del ciclo de generación. Las características de la generación termoeléctrica, como la variación horaria de la disponibilidad e intensidad de la fuente de calor (irradiancia solar), repercuten en los modos de funcionamiento del ciclo de generación que pueden clasificarse en:

- **Operación normal**. La turbina trabaja dentro de las condiciones de diseño, es decir, a una potencia que varía entre la mínima y la nominal.
- **Parada y puesta en marcha en frío**. Cuando la turbina se apaga completamente es necesaria una energía adicional ("start-up") para empezar a funcionar.
- **Operación en modo espera**. Transitoriamente puede disminuir la energía recibida por la turbina y no alcanzar el valor mínimo necesario para seguir

en funcionamiento. En aquellos casos en los que se prevé un aumento de la energía solar recibida en las siguientes horas es posible hacer uso del modo de espera. En él la turbina no se apagará completamente sino que estará en espera hasta que haya recurso solar disponible en las siguientes horas. Este modo sólo podrá utilizarse durante un número limitado de horas, y la turbina estará consumiendo la energía necesaria para no apagar el ciclo.

Rendimiento del ciclo de generación. El rendimiento de la turbina del ciclo combinado es variable y depende del nivel de carga en cada momento.

Se ha deducido el valor del rendimiento partiendo de los resultados del modelo físico de SAM (NREL [60]) utilizando los datos del rendimiento de la turbina, la potencia proporcionada a la salida de la turbina y la potencia térmica disponible a la entrada. Con estos datos se ha aproximado el valor del rendimiento de la turbina mediante una interpolación, tal y como se aprecia en la figura E.1. Puesto que a la hora de implementar el modelo no se dispone, a priori, de los valores de potencia producida sino de la potencia disponible a la entrada de la turbina, éste ha sido el valor utilizado para obtener el valor del rendimiento en cada caso a partir de la curva de interpolación. Los valores en el eje de abscisas corresponden a la potencia térmica disponible a la entrada de la turbina que oscilan entre la energía térmica mínima de trabajo de la turbina, $cut-off$, y la potencia térmica máxima, que se corresponde con el valor de la potencia eléctrica máxima de trabajo. Este último punto determinará el rendimiento máximo en la turbina. Esta relación puede aproximarse a un polinomio de cuarto grado tal y como aparece en la figura E.1.

Para valorar la validez de la aproximación se ha representado el error cometido con esta aproximación en los datos observados, en la figura E.2. Este error se define como la diferencia entre el valor estimado de potencia eléctrica a la salida de la turbina (empleando la ecuación de aproximación) y el valor observado en el modelo físico de SAM.

Almacenamiento térmico (TES). Algunas plantas termoeléctricas disponen de un sistema de almacenamiento térmico (TES por sus siglas en inglés, Thermal Energy Storage) que les permite guardar energía, generalmente, en los momentos en los que existe una gran disponibilidad de recurso solar. Posteriormente, esta energía

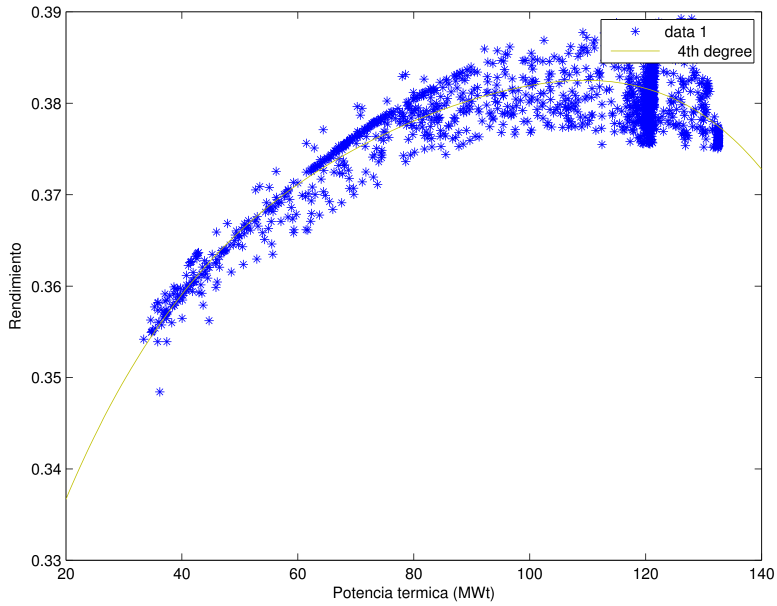


Figura E.1: Rendimiento de la turbina en función de la energía disponible.

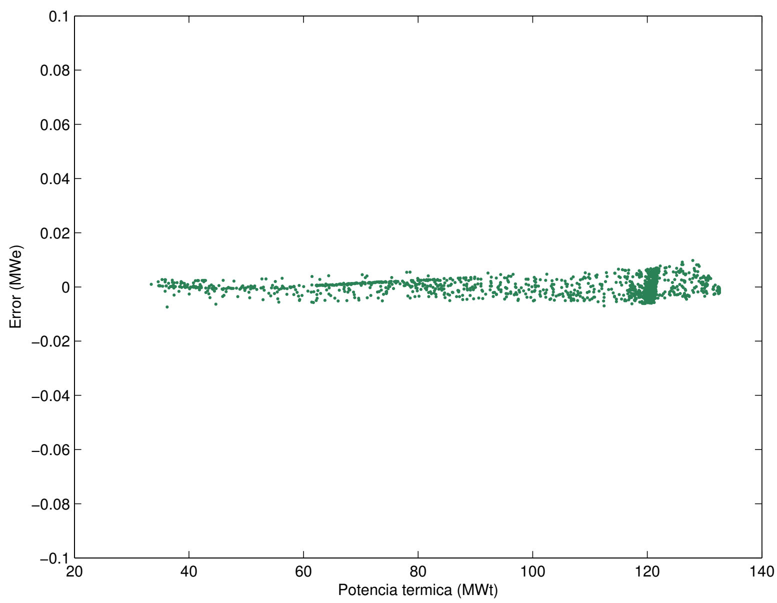


Figura E.2: Errores de la aproximación en el cálculo del rendimiento de la turbina (MWe).

térmica puede ser utilizada para incrementar la producción de energía eléctrica en aquellos periodos con escasez de recurso solar, o bien, desplazar la generación a los picos de demanda eléctrica. Por tanto, en las plantas con almacenamiento sería posible una programación del despacho de electricidad. Usaola [103] propone una optimización del uso del almacenamiento en función de los precios del mercado diario.

Existen distintas tecnologías empleadas para el almacenamiento que han sido descritas por Gil et al. [104]. Pueden encontrarse una compilación de centrales operativas con distintos tipos de almacenamiento en el trabajo realizado por Medrano et al. [105].

Dimensionado del TES. Generalmente, la capacidad del almacenamiento de las plantas termoeléctricas se define por el número de horas en las que el TES puede suministrar suficiente energía al ciclo de generación para que trabaje a plena carga en su punto de diseño. En la práctica, este número de horas es algo menor de lo especificado, puesto que no tiene en cuenta las pérdidas térmicas del almacenamiento en el cálculo de la capacidad.

La capacidad térmica del TES, E_{str}, puede ser definida en términos energéticos como la energía a la entrada de la turbina en condiciones normales de funcionamiento multiplicada por las horas de almacenamiento, tal y como se expresa en:

$$E_{str} = \frac{\dot{W}_{des}\, t_{str}}{\eta_{cycle,des}} \tag{E.35}$$

donde, $\dot{W}_{des}$, es la potencia eléctrica generada en la turbina, $\eta_{cycle,des}$ es el rendimiento en condiciones de diseño y t_{str} las horas de almacenamiento.

Pérdidas parásitas. El almacenamiento térmico tiene asociadas unas pérdidas que han sido incluidas en el modelo.

Control de la central. En el sistema de control de las centrales termoeléctricas se planifica la producción de la central en función de las predicciones de irradiancia.

Modelo producción termoeléctrica.

A continuación se presentan los resultados del modelo realizado para las centrales termoeléctricas.

Radiaciones. Los datos de DNI han sido tomados de la base de datos suministrada por NREL [60], excepto en el caso de Cádiz, en donde se han utilizado los datos de Satel-Light [61], ya que los primeros eran incorrectos. En este último caso, se ha partido de las mediciones cada media hora de los años 1996 a 2000, ambos incluidos. A partir de ellos se ha obtenido la media horaria de estos años.

Una vez obtenidos estos datos se han normalizado las series temporales mensualmente, y se han multiplicado por las mediciones de NASA [62] de las medias mensuales de irradiancia de los últimos 22 años.

Centrales termoeléctricas. Las centrales consideradas en este estudio están recogidas en la tabla E.4. Para obtener los resultados de producción han sido agrupadas por provincia para tener en cuenta los distintos niveles de irradiancia solar a lo largo de la península. Al seleccionar las instalaciones actuales y proyectadas en Protermosolar [63] se considera que la potencia instalada futura tendrá aproximadamente la misma distribución espacial, potenciándose las instalaciones con mayor recurso solar.

Nombre	Provincia	Tecnología	Potencia (MW)	Almacenamiento (horas)	Área captación solar (m^2)
PS10	Sevilla	TVS	10	1	75.000
Andasol-1	Granada	CCP	50	7,5	510.120
PS20	Sevilla	TVS	20	1	150.000
Puerto Errado I	Murcia	Fresnel	1,4	0,5	18.000
Andasol-2	Granada	CCP	50	7,5	510.120
Ibersol	Ciudad Real	CCP	50	n/a	290.000
La Risca	Badajoz	CCP	50	n/a	390.000
Extresol-1	Badajoz	CCP	50	7,5	510.120
Extresol-2	Badajoz	CCP	50	7,5	510.120
Solnova 1	Sevilla	CCP	50	n/a	350.000
Solnova 3	Sevilla	CCP	50	n/a	350.000
La Florida	Badajoz	CCP	50	7,5	550.000
Solnova 4	Sevilla	CCP	50	n/a	350.000
Majadas	Cáceres	CCP	50	n/a	380.000
La Dehesa	Badajoz	CCP	50	7,5	550.000
Palma del Río II	Córdoba	CCP	50	n/a	380.000
Manchasol-1	Ciudad Real	CCP	50	7,5	510.120
Casa de los Pinos	Cuenca	DS	1	n/a	5.280
Manchasol-2	Ciudad Real	CCP	50	7,5	510.120
Gemasolar	Sevilla	TS	20	15	304.750

Continua en la siguiente página

Tabla E.4 – Continuación

Nombre	Provincia	Tecnología	Potencia (MW)	Almacenamiento (horas)	Área captación solar (m^2)
Palma del Río I	Córdoba	CCP	50	n/a	380.000
Lebrija 1	Sevilla	CCP	50	n/a	412.000
Andasol 3	Granada	CCP	50	7,5	512.000
Helioenergy 1	Sevilla	CCP	50	6	500.000
Astexol II	Badajoz	CCP	50	7,5	510.120
Arcosol-50	Cádiz	CCP	50	7,5	510.000
Termosol-50	Cádiz	CCP	50	7,5	510.000
Aste 1A	Ciudad Real	CCP	50	8	510.120
Aste 1B	Ciudad Real	CCP	50	8	510.120
Helioenergy 2	Sevilla	CCP	50	6	500.000
Solacor 1	Córdoba	CCP	50	n/a	350.000
Puerto Errado II	Murcia	Fresnel	30	0,5	302.000
Solarcor 2	Córdoba	CCP	50	6	500.000
Helios 1	Ciudad Real	CCP	50	7	500.000
Morón	Sevilla	CCP	50	n/a	380.000
Solaben 3	Cáceres	CCP	50	4	500.000
La Africana	Córdoba	CCP	50	7,5	549.360
Guzmán	Córdoba	CCP	50	n/a	310.406
Olivenza 1	Badajoz	CCP	50	n/a	402.000

Continua en la siguiente página

Tabla E.4 – Continuación

Nombre	Provincia	Tecnología	Potencia (MW)	Almacenamiento (horas)	Área captación solar (m^2)
Orellana	Badajoz	CCP	50	n/a	405.480
Extresol-3	Badajoz	CCP	50	7,5	510.120
Helios 2	Ciudad Real	CCP	50	7	500.000
Solaben 2	Cáceres	CCP	50	n/a	350.000
Borges	Lleida	CCP+HB	22,5	n/a	181.000
Casablanca	Cáceres	CCP	50	7,5	510.120
Enerstar	Alicante	CCP	50	n/a	327.000
Extremasol 1	Badajoz	CCP	50	7,5	497.040
Arenales	Sevilla	CCP	50	7	510.000
Termosol 1	Badajoz	CCP	50	9	523.200
Termosol 2	Badajoz	CCP	50	9	523.200
Puertollano 1	Ciudad Real	DS	8	n/a	44.704
Puertollano 2	Ciudad Real	DS	10	n/a	54.080
Puertollano 3	Ciudad Real	DS	10	n/a	54.080
Puertollano 4	Ciudad Real	DS	10	n/a	54.080
Solaben 1	Cáceres	CCP	50	4	500.000
Cáceres	Cáceres	CCP	50	7,5	550.000
Puertollano 5	Ciudad Real	DS	10	n/a	54.080
Puertollano 6	Ciudad Real	DS	10	n/a	54.080

Continua en la siguiente página

Tabla E.4 – Continuación

Nombre	Provincia	Tecnología	Potencia (MW)	Almacenamiento (horas)	Área captación solar (m^2)
Puertollano 7	Ciudad Real	DS	12,4	n/a	68.768
Solaben 6	Cáceres	CCP	50	n/a	350.000
Alcázar	Ciudad Real	TS	50	20	1.082.640

Tabla E.4: Centrales termoeléctricas consideradas en el modelo

Características técnicas. Los valores de rendimiento y pérdidas de las centrales se han tomado del modelo de SAM (NREL [60]).

Programación del modelo. El modelado físico está basado en el funcionamiento actual de las centrales termoeléctricas. En él se utilizan las predicciones de irradiancia para programar la producción. Se ha considerado que las plantas utilizarán la energía solar para calentar el campo solar en las primeras horas del día. Si la energía solar no es suficiente se utilizará la caldera auxiliar. En los casos en los que la energía solar sea superior a la necesaria para producir a potencia nominal se almacenará la energía disponible. Cuando exista energía almacenada y el recurso solar disponible no sea suficiente para producir energía a potencia nominal, o no exista recurso solar, se utilizará la energía almacenada disponible. Se han considerado en el modelo:

- Las pérdidas del campo solar tanto ópticas como constantes, y del fluido caloportador.
- La energía de calentamiento del campo solar.
- Las pérdidas en el almacenamiento.
- Un rendimiento variable para la turbina que depende de la energía térmica disponible.
- Un rendimiento de conversión energética de la energía que se obtiene del almacenamiento y que es utilizada para producir electricidad.
- Rendimiento del almacenamiento de energía térmica. Existen pérdidas al almacenar la energía térmica que procede del campo solar.
- Consumos de energía en la planta.

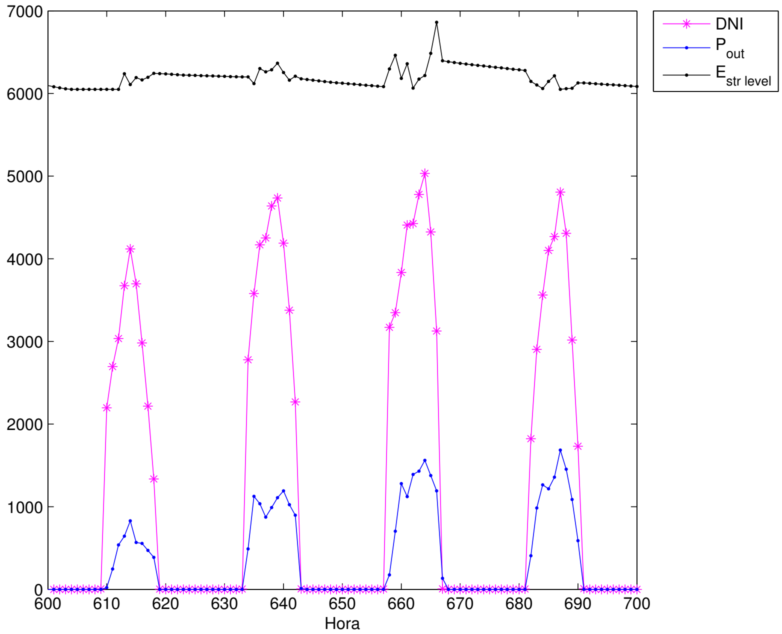
No se ha supuesto en ningún caso una programación de la producción en función de los precios del mercado, sino que se ha simulado el funcionamiento habitual de estas centrales de manera que se maximice la energía producida partiendo del recurso solar disponible. La programación de la producción en función de la curva de demanda se realizará en posteriores trabajos.

Resultados del modelo termoeléctrico. Para obtener la producción peninsular de la tecnología termoeléctrica se han tomado radiaciones de las distintas ubicaciones de las plantas agrupándolas por localidad, es decir, todas las plantas de la misma provincia se han agregado y simulado como si fuesen sólo una en cuanto a potencia, área de captación del campo solar y capacidad de almacenamiento. Posteriormente, para obtener la producción termoeléctrica en el caso base se han utilizado los resultados de la simulación del modelo, normalizándolos y escalándolos según la producción de energía anual establecida en el PANER.

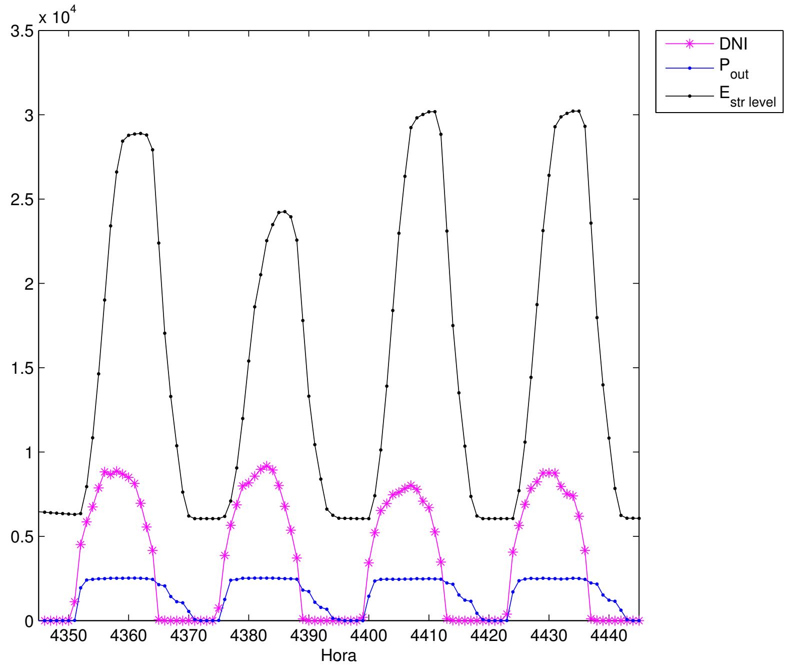
En la tabla E.5 se muestran las hipótesis asumidas para las distintas localidades consideradas, así como los resultados obtenidos en la simulación para cada una de ellas y los totales. Los parámetros considerados son el resultado de la agregación de todos los parques por provincia. Para calcular la potencia nominal total se han sumado las de todas las centrales individuales. En el caso de la capacidad de almacenamiento se han obtenido los MWh equivalentes de cada planta y se han agregado para obtener el almacenamiento total de la provincia. Las horas equivalentes y la energía generada han sido resultado de la simulación empleando el modelo propuesto. Las horas equivalentes de funcionamiento se definen como la ratio entre la energía generada y la potencia instalada. Esta ratio da una idea de cuántas horas equivalentes estaría funcionando la planta a la potencia nominal.

En la figura E.3 se representan cuatro días típicos de producción invernales, figura E.3(1) y estivales, figura E.3(2). El recurso solar disponible está representado en magenta e indica la suma de la irradiancia normal directa disponible en todas las localidades estudiadas. En negro se ha dibujado la energía disponible en el almacenamiento y en azul la energía producida. Ambas curvas son el resultado de la agregación de la producción y el almacenamiento a escala nacional, y es por ello que la curva de producción a partir del almacenamiento, cuando no existe recurso local disponible, está definida a trazos. Se aprecia que el recurso solar disponible es mucho más abundante en verano que en invierno, por lo que la energía del almacenamiento es empleada para suministrar energía eléctrica tras la puesta de sol. Puede observarse que en el almacenamiento nunca hay una energía disponible por debajo de un nivel mínimo, esto es debido a que el sistema debe evitar la solidificación de las sales del almacenamiento. En el caso de que no exista recurso solar disponible suficiente para ello se hace uso de la caldera auxiliar.

En la figura E.4 se muestran las curvas de producción e irradiancia, y, en los



(1) Días invierno



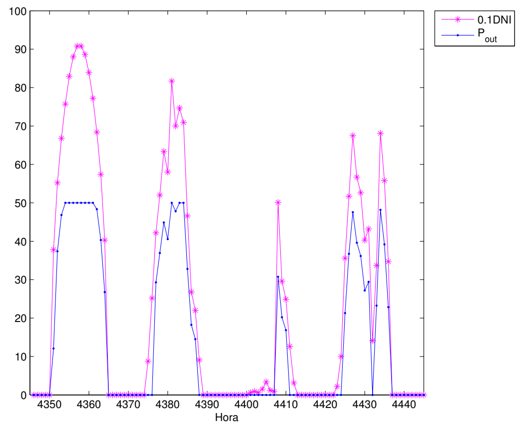
(2) Días verano

Figura E.3: Producción anual (MW), irradiancia(MW/m^2) y almacenamiento termosolar (MWh) de la producción agregada en el sistema peninsular en días tipo.

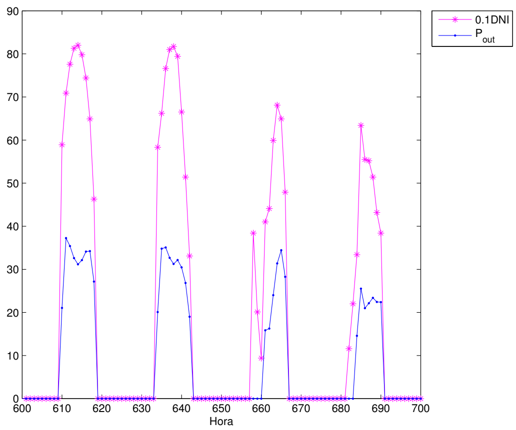
Provincia	Potencia (MW)	Capacidad almacenamiento (MWh)	Horas equivalentes	Energía generada (GWh)
Alicante	50,0	0,0	1478,71	96,75
Badajoz	600,0	3525,0	1950,80	1558,96
Cáceres	350,0	1150,0	1612,16	779,90
Cádiz	100,0	750,0	1640,26	233,53
Ciudad Real	470,4	3250,0	2095,19	1295,78
Córdoba	300,0	675,0	1794,87	702,95
Granada	150,0	1125,0	2431,72	457,53
Lleida	22,5	0,0	1499,01	45,79
Murcia	31,4	15,7	1462,02	66,03
Sevilla	450,0	1280,0	2099,54	1187,79
Total	2524,3	11770,7	2545	6426,29

Tabla E.5: Resultados anuales del modelado termosolar

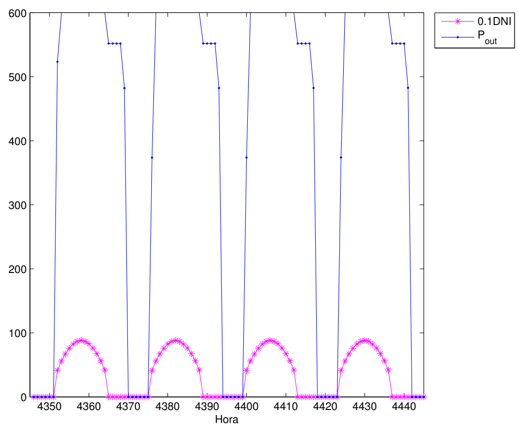
casos en los que existe las de almacenamiento, para los emplazamientos simulados. En ellas se representa la energía agregada de cada provincia. Se han seleccionado algunos días característicos de verano e invierno. En las figuras presentadas se puede apreciar las diferencias existentes entre las localidades que poseen o no un sistema de almacenamiento térmico. En el caso de que no se disponga de almacenamiento, tal y como sucede en Alicante, figuras E.4(1) y E.4(2), la producción eléctrica se limita a las horas en las que existe recurso solar. En las localidades que poseen almacenamiento térmico, se observa que existe producción eléctrica en las horas nocturnas. Esta producción es especialmente importante en verano, puesto que la abundancia de recurso solar permite llenar el sistema de almacenamiento, figura E.4(4), para producir durante varias horas en las que no existe disponibilidad de recurso solar, figura E.4(3). Las diferencias de irradiancia en las distintas localidades son especialmente acentuadas en los días de invierno, en los que se aprecian algunos días en los que no existe siquiera recurso solar para producir energía eléctrica, figura E.4(29).



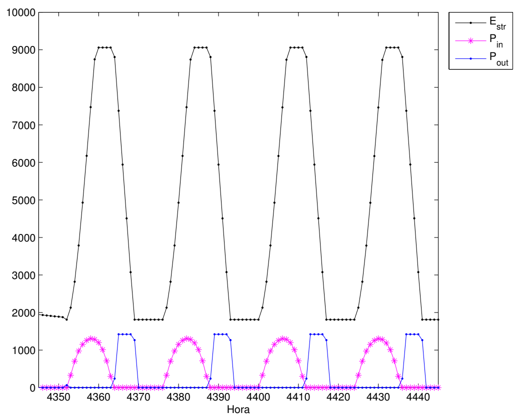
(1) Producción Alicante verano



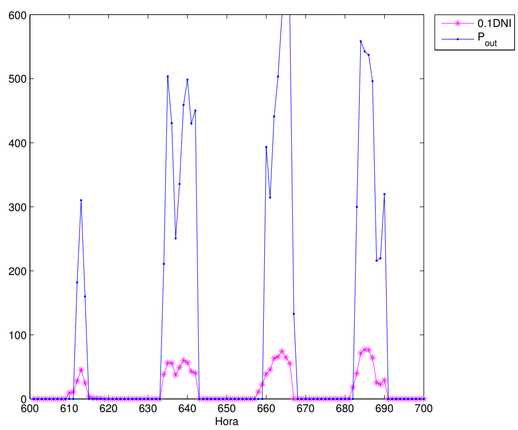
(2) Producción Alicante invierno



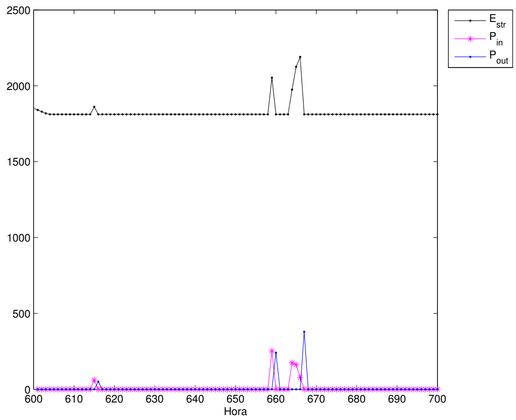
(3) Producción Badajoz verano



(4) Almacenamiento Badajoz verano

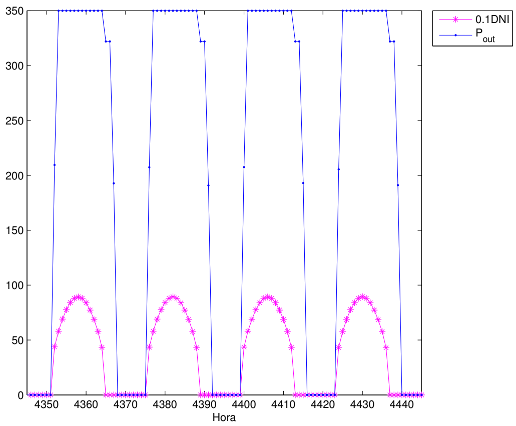


(5) Producción Badajoz invierno

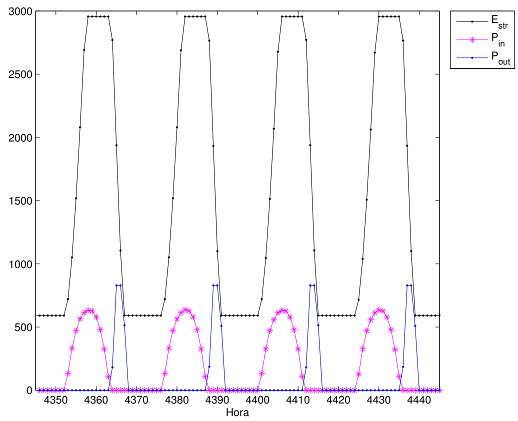


(6) Almacenamiento Badajoz invierno

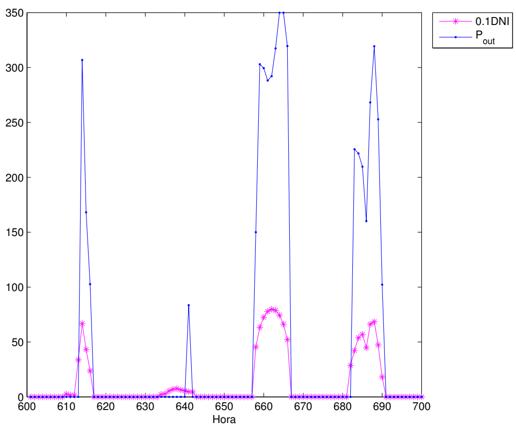
Figura E.4: Producción y almacenamiento CSP en distintas localizaciones



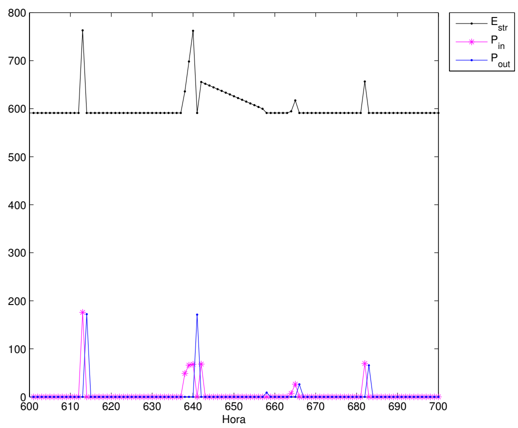
(7) Producción Cáceres verano



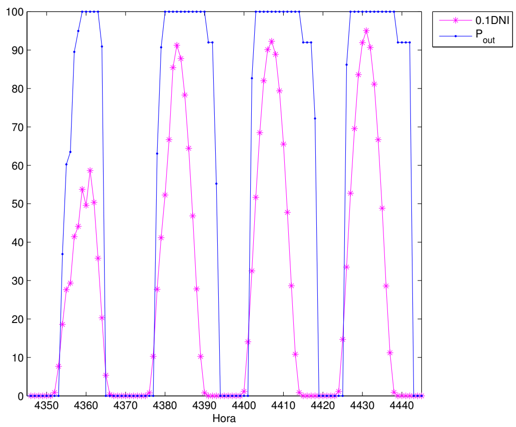
(8) Almacenamiento Cáceres verano



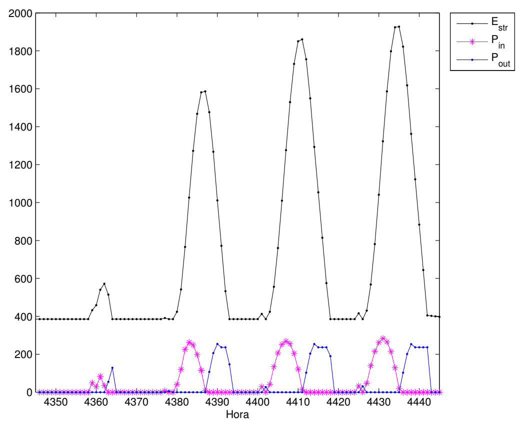
(9) Producción Cáceres invierno



(10) Almacenamiento Cáceres invierno

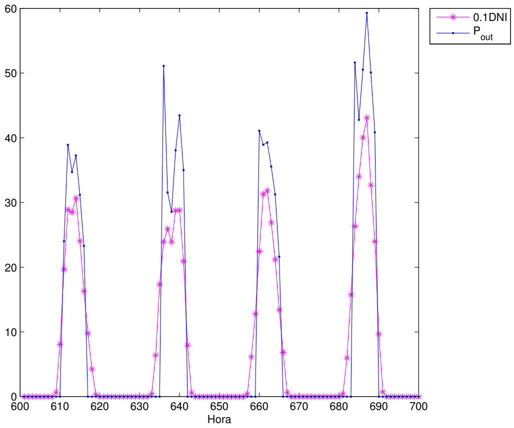


(11) Producción Cádiz verano

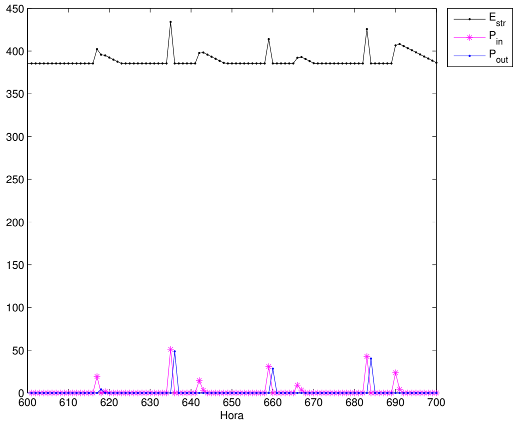


(12) Almacenamiento Cádiz verano

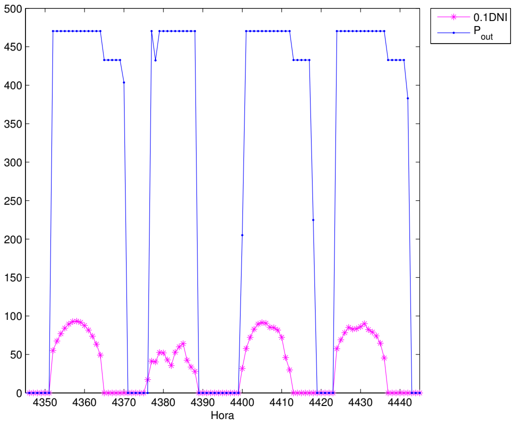
Figura E.4: Producción y almacenamiento CSP en distintas localizaciones (continuación).



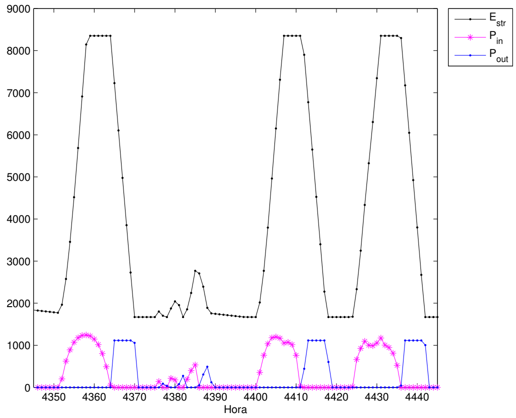
(13) Producción Cádiz invierno



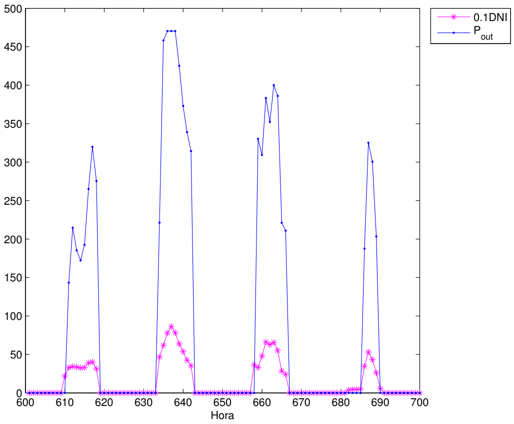
(14) Almacenamiento Cádiz invierno



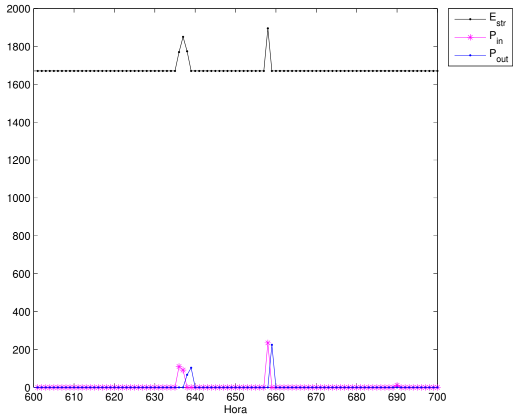
(15) Producción Ciudad Real verano



(16) Almacenamiento C. Real verano

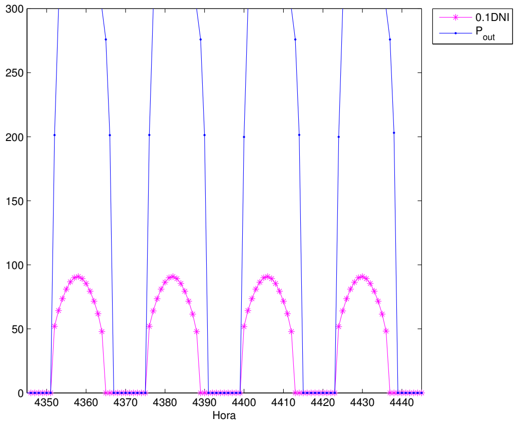


(17) Producción C. Real invierno

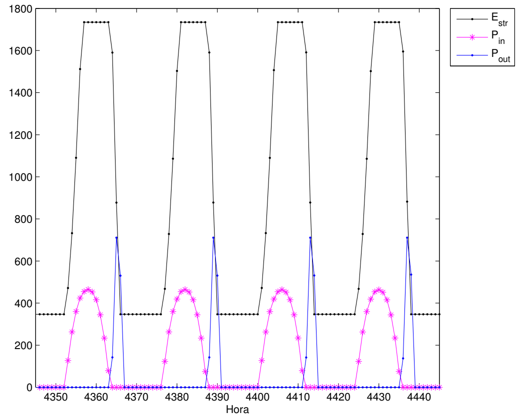


(18) Almacenamiento C. Real invierno

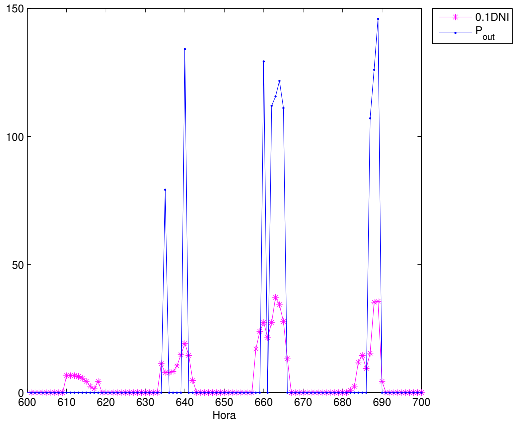
Figura E.4: Producción y almacenamiento CSP en distintas localizaciones (continuación).



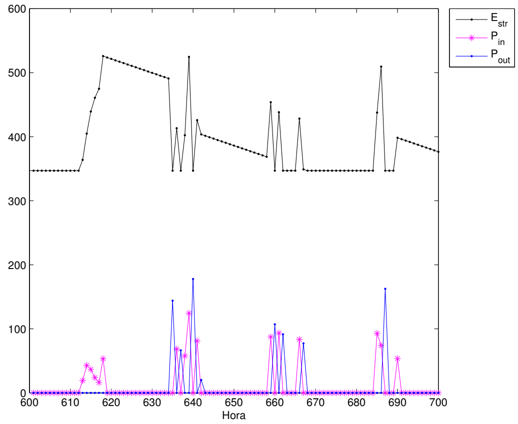
(19) Producción Córdoba verano



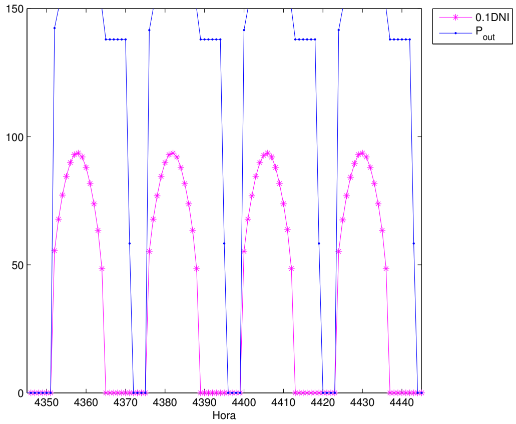
(20) Almacenamiento Córdoba verano



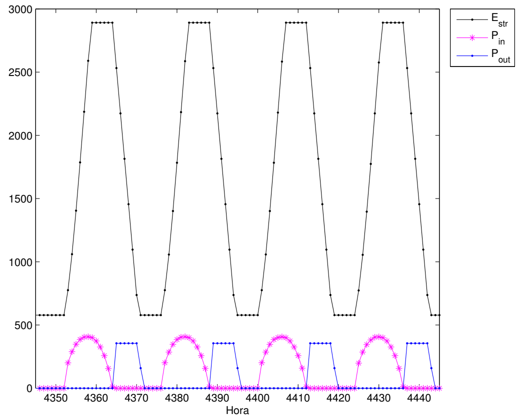
(21) Producción Córdoba invierno



(22) Almacenamiento Córdoba invierno

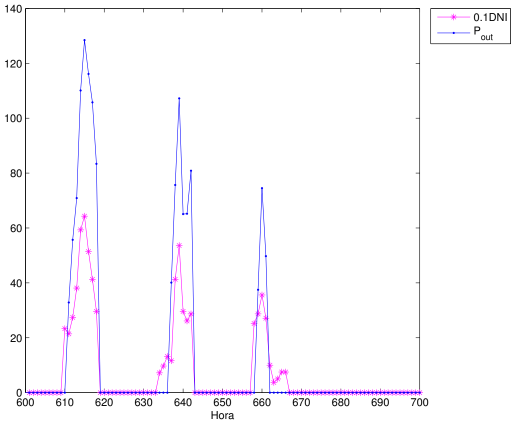


(23) Producción Granada verano

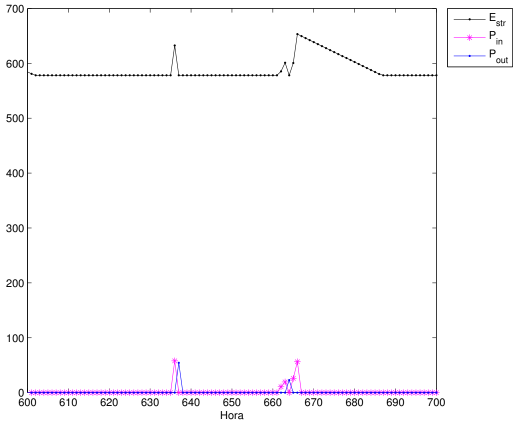


(24) Almacenamiento Granada verano

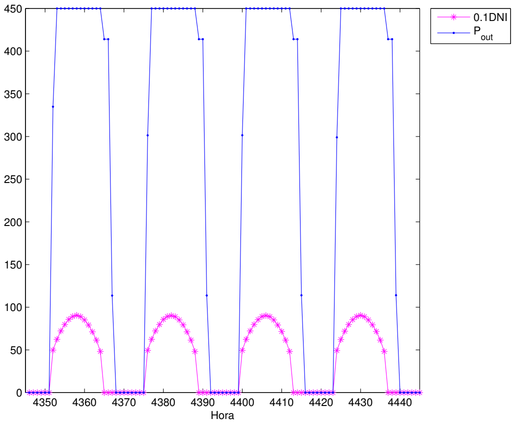
Figura E.4: Producción y almacenamiento CSP en distintas localizaciones (continuación).



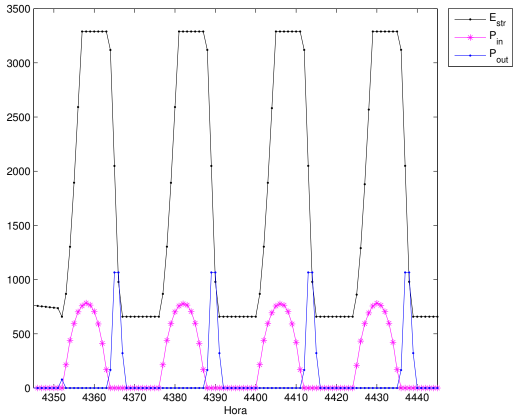
(25) Producción Granada invierno



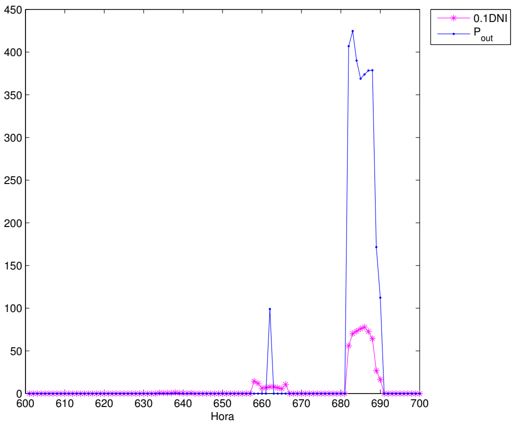
(26) Almacenamiento Granada invierno



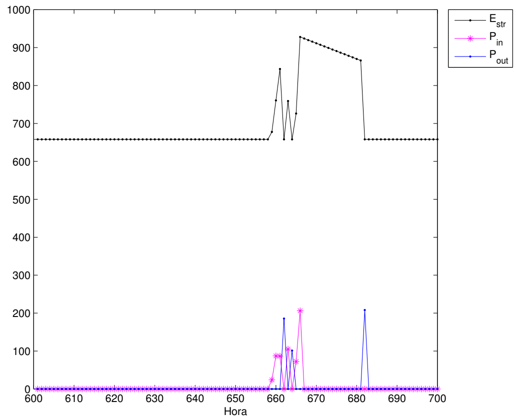
(27) Producción Sevilla verano



(28) Almacenamiento Sevilla verano



(29) Producción Sevilla invierno



(30) Almacenamiento Sevilla invierno

Figura E.4: Producción y almacenamiento CSP en distintas localizaciones.

E.2.2 Modelado de la producción hidráulica

El modelado de la producción hidráulica es especialmente complejo, debido a la naturaleza estocástica de las lluvias, a que sus afluentes pueden variar de hora a hora y a la dispersión geográfica. A pesar de ello, la posibilidad de almacenamiento hace que la energía hidráulica disponible varíe suavemente. En general, estas variaciones pueden considerarse en periodos, ya sean semanales, estacionales o anuales. Las fluctuaciones de la potencia hidráulica de los distintos embalses pueden tener correlaciones temporales y espaciales entre sí.

En el caso español la programación hidráulica es especialmente compleja (López [106]), debido al régimen irregular de lluvias, que puede variar de año en año, y a la distribución irregular de la pluviosidad a largo de la península, que posee regiones muy secas y otras húmedas. Además, la posible escasez de agua y el uso compartido de los embalses para usos distintos de la producción eléctrica, ya sea riego, consumo humano u otros, limita la disponibilidad de este recurso para la generación de electricidad, que está restringida por las exigencias de las distintas confederaciones hidrográficas.

Los embalses pueden clasificarse en anuales e hiperanuales. Los anuales son aquellos que tienen un ciclo anual, es decir, que se repite todos los años. En estos embalses el nivel de reserva tiene un ciclo estacional, que comienza con poco volumen al inicio de las lluvias de otoño, se mantienen bajos hasta la primavera, momento en el que van subiendo de tal forma que están llenos o casi llenos al comienzo del verano, vaciándose a lo largo del verano. Por otro lado, los embalses hiperanuales permiten almacenar las aportaciones en años húmedos para consumirlas en años secos. Suelen ser embalses muy grandes con unas exigencias tan fuertes de la Confederación Hidrográfica a la que pertenecen, que permiten muy poca programación hidráulica por parte de la empresa eléctrica propietaria de la central.

Además los embalses pueden ser fluyentes o no fluyentes, dependiendo de su capacidad de regulación. Los embalses fluyentes no permiten embalsar agua debido a su tamaño y las aportaciones que reciben. Habitualmente se explotan a cotas altas para que las centrales asociadas funcionen con el máximo rendimiento. Estos embalses no admiten regulación.

Generalmente, los embalses fluyentes y no fluyentes suelen modelarse de manera separada, puesto que los primeros dependerán de la pluviosidad, turbinando la energía disponible para obtener un máximo rendimiento, y los segundos suelen producir energía en función de la programación hidráulica realizada por las compañías generadoras. Por tanto, ésta es la aproximación tomada en este modelo, que trata de manera separada los dos tipos de generación.

Parámetros del modelo hidráulico

Para determinar la energía disponible en un momento determinado, la herramienta Wilmar utiliza como datos de entrada, las aportaciones hidráulicas, los niveles del embalse y la producción en cada hora, de manera que ha de cumplirse la siguiente igualdad:

$$Aportaciones(h) = Nivel_{embalse}(h+1) - Nivel_{embalse}(h) - Producción(h) \quad (E.36)$$

Las aportaciones hidráulicas son modeladas a partir del valor de producible hidráulico y del índice de producible hidráulico que se definen a continuación, REE [107]:

- **Producible hidráulico** Cantidad máxima de energía eléctrica que teóricamente se podría producir considerando las aportaciones hidráulicas registradas durante un determinado período de tiempo y una vez deducidas las detracciones de agua realizadas para riego o para otros usos distintos de la producción de energía eléctrica.

- **Índice de producible hidráulico** Cociente entre la energía producible y la energía producible media, referidas ambas a un mismo periodo y a un mismo equipo hidroeléctrico. Un índice menor que uno indica que el año es seco, mientras un índice mayor indica que es húmedo.

En el caso que nos ocupa el producible hidráulico es equivalente a las aportaciones a los embalses, pues tiene en cuenta éstas una vez descontada el agua necesaria para otros usos. Además de este parámetro se consideran las capacidades de los embalses, las series históricas de los niveles y la mínima cantidad de agua embalsada permitida.

Debido al régimen irregular de lluvias los años meteorológicos se clasifican en función del índice de producible hidráulico en secos, medios o húmedos. En este caso se utilizará esta tipificación y se realizarán simulaciones para cada clase.

Modelado de series temporales de producción hidráulica

En la herramienta de planificación Wilmar la energía fluyente es modelada a partir de series temporales de producción. Para hallar estos valores el modelado se ha basado en series históricas. Para respetar la variabilidad de las series no se han tomado valores medios de distintos años, sino que se ha escogido un año de referencia (húmedo, medio o seco), y se han utilizado las series de producción normalizadas, dividiendo la producción horaria por la producción total anual. Se ha llevado a cabo esta aproximación para tener en cuenta las distintas tendencias en las series temporales en función de la pluviosidad del año considerado. En la figura E.5 se ha representado la producción hidráulica fluyente durante el año 2012 para toda la península. Se puede apreciar la estacionalidad de las precipitaciones que disminuyen drásticamente en verano, y alcanzan su máximo valor en primavera y otoño.

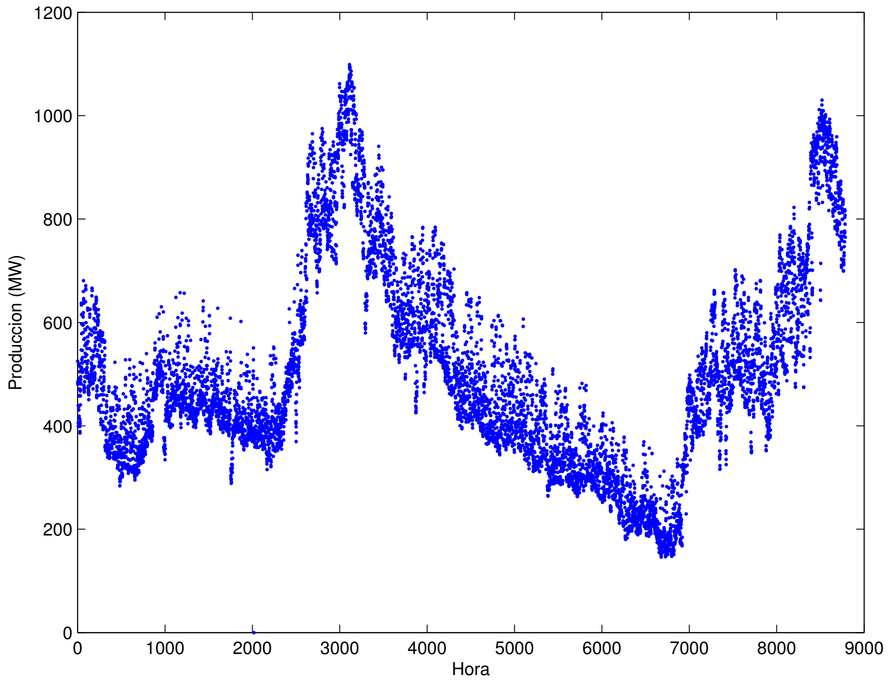


Figura E.5: Producción hidroeléctrica régimen especial año 2012 (MW)

Los embalses no fluyentes se han considerado de manera agregada. Puesto que es complicado simular las restricciones de las Confederaciones Hidrográficas, la variabilidad territorial y las diferencias interanuales de la pluviosidad, se ha optado por usar las series históricas de niveles de los embalses y producible hidráulico.

En un modelo de programación horaria el uso de la energía hidroeléctrica ha de ser limitado puesto que el recurso es limitado y su coste marginal es cero. Para que no haya un consumo excesivo de esta energía que no tenga en cuenta las restricciones de uso es necesario hacer una programación de la producción. De lo contrario, debido al bajo precio marginal de la energía hidroeléctrica se emplearía toda la energía disponible en los embalses durante el periodo de optimización, de modo que las reservas estarían agotadas al comienzo del periodo de optimización siguiente. Teniendo en cuenta que la energía hidráulica producida tendrá el mismo valor que el de la energía térmica a la que sustituya se define un *precio sombra* para la producción hidroeléctrica. Este precio representa el coste de oportunidad de producir o consumir un bien o servicio. Matemáticamente, los precios sombra son proporcionados por la solución óptima del problema dual, y representan la variación de la función objetivo cuando se cuenta con una unidad adicional de un cierto recurso limitado, es decir, son la contribución al beneficio de cierto recurso. Este precio estará indexado, por un lado, al coste marginal de la energía térmica, y, por otro, a la disponibilidad de la energía hidráulica, esto es, a la cantidad de energía embalsada y a su coste de producción. Para simular este fenómeno, se ha definido un precio sombra de referencia, Ps_{ref}^{hidro}, que estará relacionado con el precio medio del mercado diario (o precio de la unidad térmica a la que sustituye la energía hidráulica), y en consecuencia, será distinto para cada escenario. Además se han considerado niveles de reservas de los embalses de referencia teniendo en cuenta los niveles históricos observados en años meteorológicos tipo equivalentes. En el caso de que el consumo de energía hidráulica sea muy elevado y el nivel de embalsado obtenido tras la simulación sea inferior al nivel del año histórico de referencia, el precio sombra de la producción hidráulica aumentará respecto al de referencia, y en caso contrario disminuirá. Por tanto, el precio sombra, $Ps_{i,t}^{hidro}$ será dinámico y estará definido para cada hora en función de los niveles de agua embalsada, $V_{I^{hidro},t}^{hidro}$, siguiendo la ecuación (E.37), donde $V_{ref,t}^{hidro}$ es el nivel de agua embalsada en la hora t del año de referencia y $v_i^{Hidromax}$ la capacidad máxima de embalsado. Ambas variables están expresadas en MWh.

$$Sp_{i,t}^{hydro} = MAX(1, Sp_{ref}^{hydro} + 500\left(\frac{V_{I^{hydro},t}^{hydro} - V_{ref,t}^{hydro}}{v_i^{Hydromax}}\right) \qquad \text{(E.37)}$$

Año	Año meteorológico	Producible (GWh)	Índice de producible
2003	Normal	33213	1,15
2004	Muy seco	22693	0,79
2005	Extremadamente seco	12980	0,45
2006	Normal/Seco	23286	0,82
2007	Seco	18416	0,65
2008	Seco	18945	0,67
2009	Seco	22262	0,79
2010	Muy húmedo	36174	1,29

Tabla E.6: Datos históricos de producible hidráulico.

Clasificación de años meteorológicos históricos

Puesto que en los escenarios de producción futura se han tenido en cuenta distintos tipos de años meteorológicos, se han escogido los niveles de reserva y producible a partir de los datos históricos disponibles. En la tabla E.6 se presentan los datos de producibles de los años 2004 al 2010, junto con su tipificación meteorológica.

Los años escogidos como referencia están resaltados en azul, siendo el 2005 escogido para el año seco, 2006 para el medio y 2010 para el húmedo. Para los datos de aportaciones de la hidráulica fluyente se han considerado los datos históricos de los años 2006 al 2010, el año seco de referencia ha sido en este caso el 2007.

Correlación entre la producción hidráulica y la eólica

Tal y como se ha descrito anteriormente el recurso hidráulico disponible tiene un acentuado comportamiento estacional. Dado que la potencia hidráulica proviene en la mayor parte de los casos de grandes embalses, la correlación con la energía eólica a corto plazo no es relevante para la operación del sistema eléctrico. Sin embargo, la correlación anual de las producciones eólica e hidráulica podría tener influencia en la integración de la energía eólica en el sistema eléctrico. Si la correlación es positiva, los años secos tendrán menos producción eólica lo que sería perjudicial para dicha integración. En este caso se ha tenido en cuenta una correlación positiva entre ambas producciones que tendrá efectos en la programación horaria, suponiendo que a mayor pluviosidad mayor viento, y en sentido opuesto, a menores precipitaciones menor producción eólica.

E.2.3 Series de producción de otras energías renovables

A continuación se presentarán las principales características de las series de producción de otras energías renovables. Las series de producción futura están basadas en series históricas horarias.

Producción fotovoltaica

La producción fotovoltaica es proporcional al nivel de radiación en las áreas de instalación de las plantas fotovoltaicas. Como ejemplo de su periodicidad, las curvas de producción fotovoltaica en el año 2012 están representadas en la figura E.6. Para estimar la producción en el año 2020 se han usado los datos históricos del año 2012 que recogen la producción nacional. Estas curvas han sido normalizadas, y serán multiplicadas por la producción total estimada por el PANER.

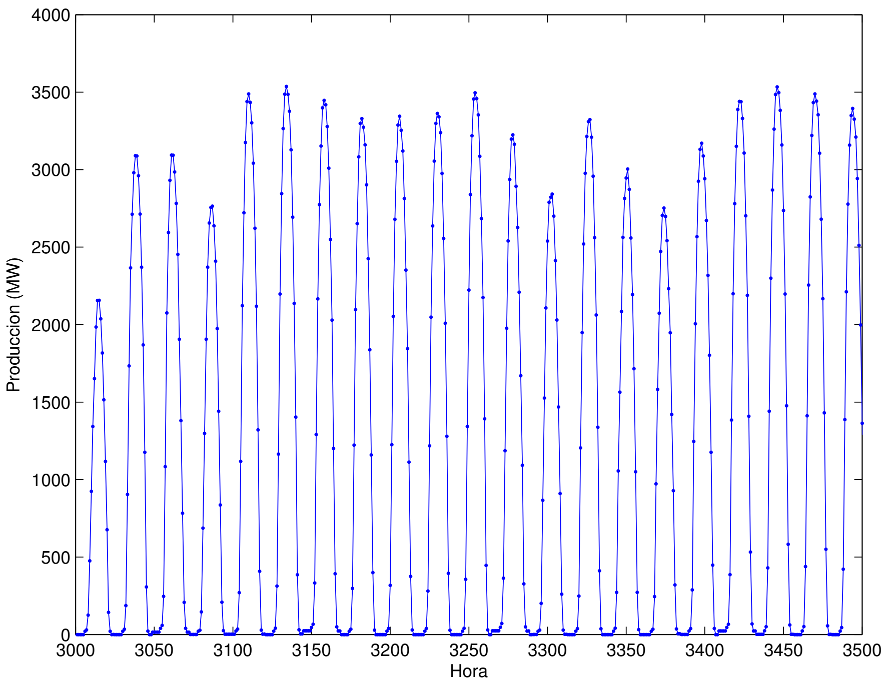


Figura E.6: Detalle de la producción fotovoltaica en el año 2012 (horas 3000-3500)

Producción con biomasa

La producción anual de energía que proviene de la biomasa apenas varía a lo largo del año. Esto es debido a que su producción sólo depende de la disponibilidad de combustible. La curva de producción en el año 2012 está representada en la figura E.7. Para estimar la producción futura se han tomado las series de producción normalizadas en ese año.

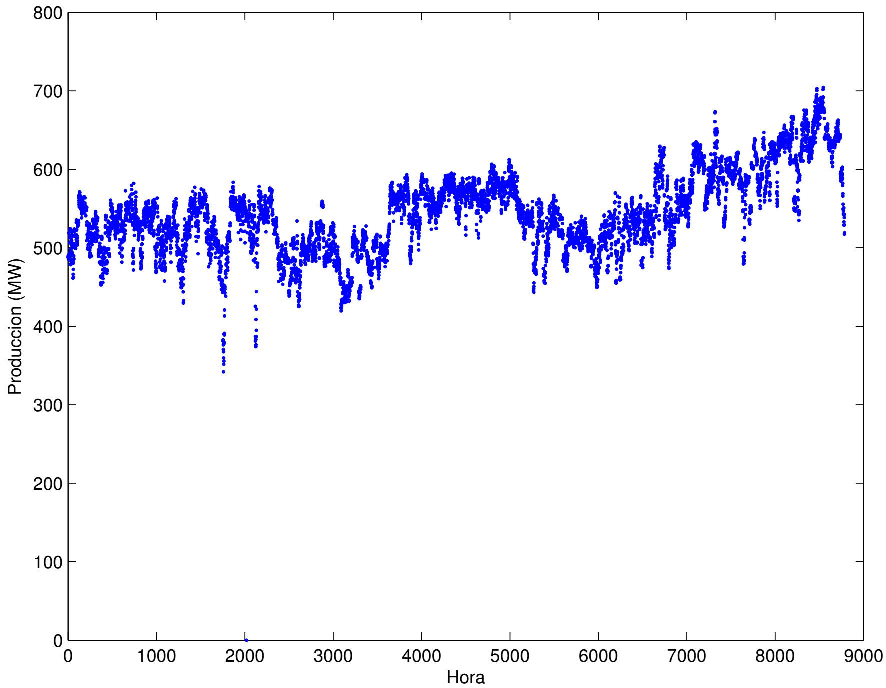


Figura E.7: Producción de biomasa en el año 2012 (MW).

Producción eólica

La energía eólica es tremendamente variable. En la figura E.8 se ha representado la producción a lo largo del año 2012, que varía desde 474 MW hasta 16325 MW.

En el modelado de la producción eólica se han utilizado también series históricas, en este caso de los años 2008 al 2010. A partir de ellas se han creado dos tipos de series de producción, una con viento abundante basada en los datos del año 2010, y en la cual el factor de capacidad (ratio entre la energía producida y la potencia instalada multiplicada por el número de horas del periodo considerado,

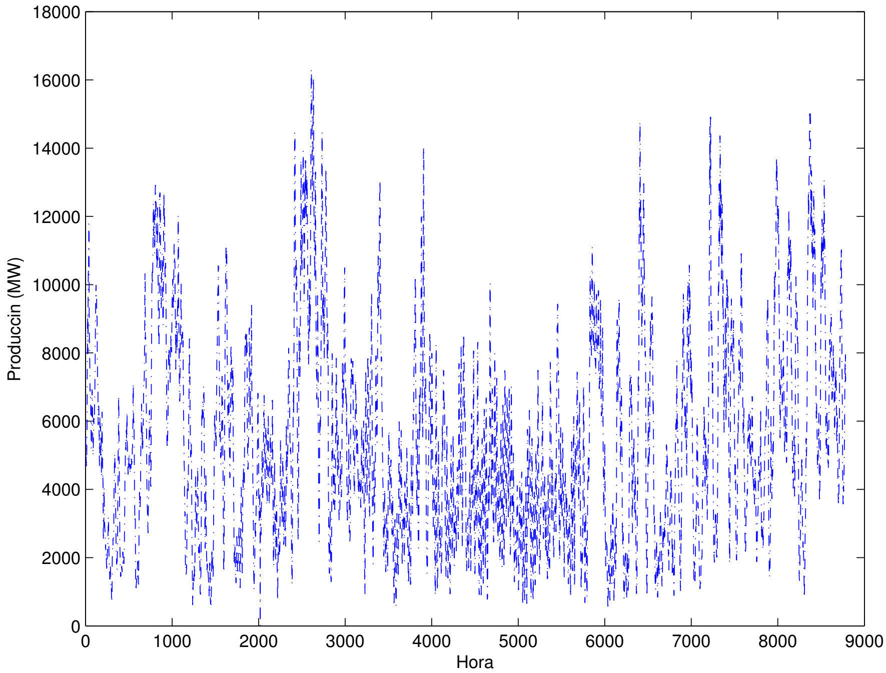


Figura E.8: Producción de energía eólica en el año 2012 (MW)

ecuación (E.39)) fue superior a los de las otras series disponibles; y otra que está basada en los datos de producción del año 2008, y representa la tendencia habitual de la distribución del viento. En ambos casos se han normalizado las series para respetar la variabilidad, pues si se aplicara el valor medio de producción de distintos años la curva obtenida sería más suave que las producciones reales.

E.2.4 Demanda

Para la estimación de la demanda se han utilizado a su vez series históricas, en este caso del año 2009. Los datos horarios se han normalizado dividiéndolos por la suma de la demanda anual para preservar su variabilidad y respetar su tendencia cíclica. De esta manera se representan tanto las horas punta y valle, como los distintos niveles de demanda entre los fines de semana y los días laborales, y la estacionalidad de la demanda. Posteriormente, se multiplicarán estas series por el valor anual de la demanda estimado para cada uno de los escenarios de la simulación. En la figura E.9 está dibujada la curva de la demanda eléctrica de las series históricas empleadas. Se han representado tan sólo unas horas para apreciar la variación semanal de su valor.

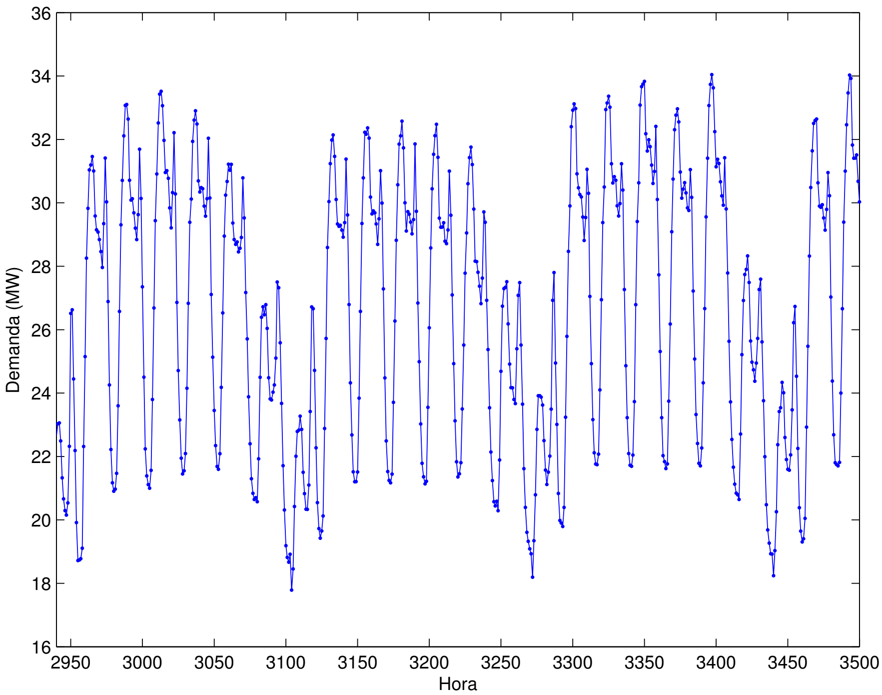


Figura E.9: Detalle de curva de la demanda en el año 2009 (MW)

E.2.5 Reservas

El modelo planteado en este trabajo realiza una optimización determinista del parque de generación español para determinar la programación horaria. Puesto que al no tener variables estocásticas no es posible deducir los valores reales de las reservas secundaria y terciaria a partir de los errores de predicción, se ha realizado una aproximación a las reservas, definiendo unas bandas fijas de reservas secundaria y terciaria a subir y bajar.

En el P.O 1.5. (BOE [108]) se define el método de asignación de reservas como sigue. La reserva secundaria será determinada por el operador del sistema en función de la evolución temporal previsible de la demanda y del fallo probable esperado según la potencia y los equipos de generadores acoplados. La regulación secundaria actuará desde los 30 segundos hasta 15 minutos hasta que su uso sea sustituido por la reserva terciaria. Según las recomendaciones de ENTSO-E el requerimiento mínimo de reserva de regulación secundaria viene determinado por la fórmula:

$$R = \sqrt{aL_{max} + b^2} - b \tag{E.38}$$

donde L_{max} es el nivel de demanda previsto en el área de control correspondiente al sistema peninsular español. Los parámetros a (10 MW) y b (150 MW) se han determinado empíricamente. La reserva secundaria a bajar se establecerá, atendiendo a la evolución creciente o decreciente de la demanda, entre el 40 y el 100 % de la reserva a subir. Además se dotará de mayor volumen de reserva en las horas que presentan puntos de inflexión de la curva de demanda peninsular.

La reserva mínima necesaria de regulación terciaria a subir en cada período de programación será, como referencia, igual a la pérdida máxima de producción provocada de forma directa por el fallo simple de un elemento del sistema eléctrico, más un 2 % del valor de la demanda prevista en cada periodo de programación. La reserva terciaria a bajar se establecerá, en función de las condiciones de operación, entre el 40 y el 100 % de la reserva a subir.

En la figura E.10 están representados los requerimientos de reserva a bajar y subir para el año 2012. De manera análoga, en la figura E.11 se muestran los requerimientos de reserva terciaria.

Los valores asignados a las reservas secundaria y terciaria están resumidos en la tabla E.7, y se han seleccionado en función de los valores del año 2012.

Reserva (MW)	Secundaria	Terciaria
Subir	750	1500
Bajar	550	1500

Tabla E.7: Requerimientos de reserva

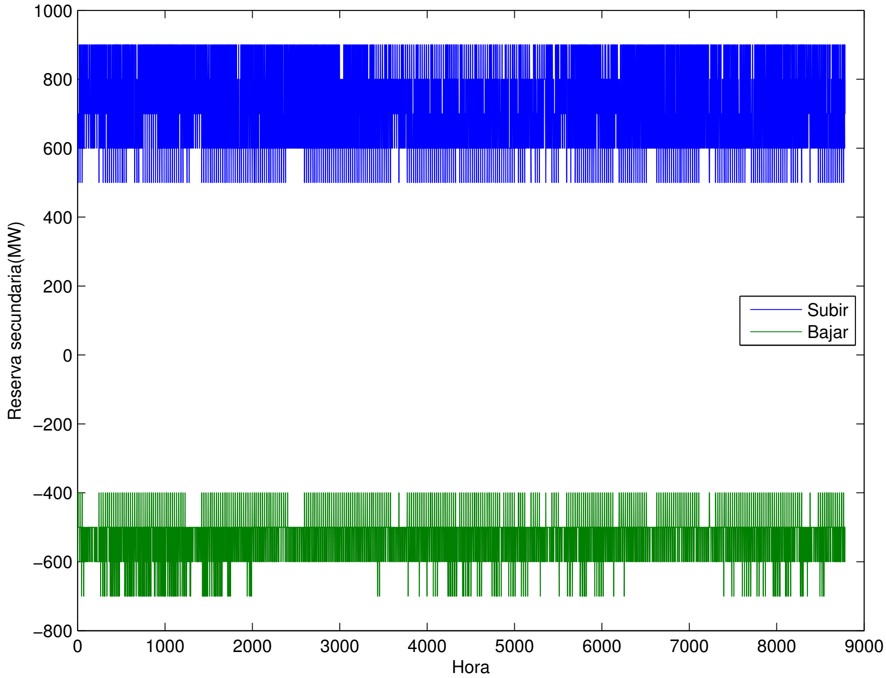


Figura E.10: Reserva secundaria en el año 2012 (MW)

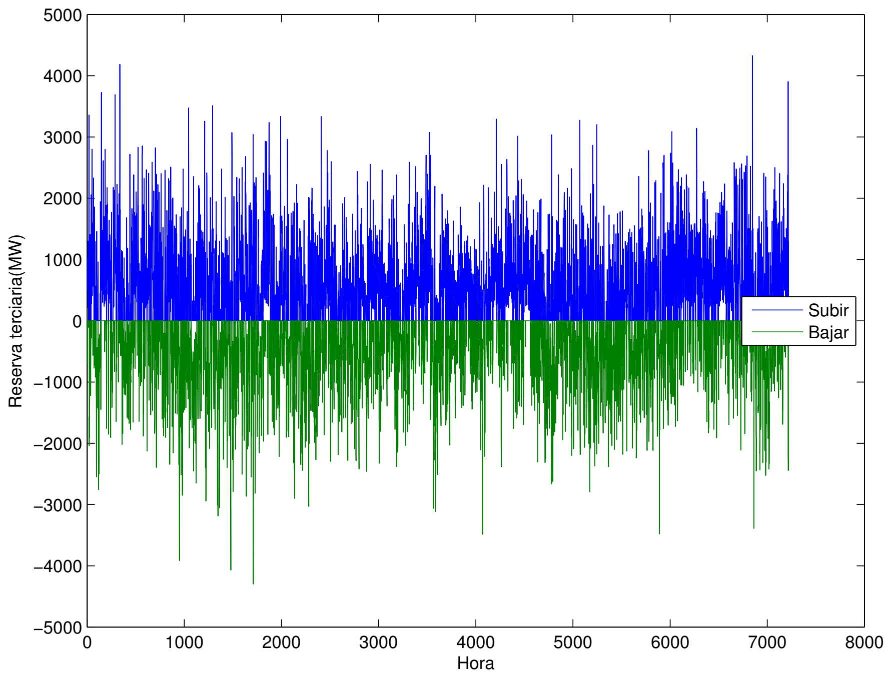


Figura E.11: Reserva terciaria en el año 2012 (MW)

E.3 Resultados

E.3.1 Introducción

Mediante este modelo se ha obtenido la programación horaria de las unidades de generación (“unit commitment”) del sistema eléctrico español en el año 2020. Para obtener los resultados se ha utilizado el software de optimización GAMS, que ha resuelto el problema planteado por la herramienta Wilmar mediante el “solver” CPLEX. Ha sido necesario adaptar su formulación al sistema eléctrico español tanto en los datos como en su funcionamiento. Sirva como ejemplo, la consideración de las rampas de la tecnología nuclear y sus restricciones temporales que el modelo no contemplaba, lo que, consecuentemente, ocasionaba problemas de factibilidad. Así mismo, se ha introducido un modelo de la tecnología termoeléctrica que proporciona datos de producción energética horaria a nivel nacional, a partir de las radiaciones solares, la potencia instalada y la capacidad del sistema de almacenamiento térmico. Este estudio es una primera aproximación al análisis del sistema eléctrico con alta penetración de renovables, por lo que se ha aplicado un modelo determinista que tiene en cuenta la participación en el mercado diario de una alta proporción de renovables, así como las rampas de las centrales convencionales.

En el modelado de los escenarios de producción futura se han empleado los supuestos establecidos por la Unión Europea y plasmados por el gobierno español en el Plan de Acción Nacional de Energías Renovables (PANER) (Ministry of Industry, Energy and Tourism, MINETUR [64]), en donde se considera que la ratio de producción de energía de origen renovable respecto a la producción bruta será de un 36 %. Además se han considerado distintos escenarios de precios de combustibles y derechos de emisiones de dióxido de carbono, junto con distintos escenarios meteorológicos anuales y un escenario adicional en el que se tienen en cuenta las condiciones económicas actuales y su influencia en, por un lado, la estimación de la demanda, y, por otro lado, la consecución de los objetivos establecidos en el PANER en cuanto a capacidad renovable instalada.

A lo largo de esta sección se describirán los escenarios en detalle y se expondrán los resultados obtenidos.

Tecnología	Potencia instalada (MW)
Carbón	11018
Nuclear	7181
Fuel / Gas	1453
Ciclo combinado	25274
Hidráulica convencional	17761
Cogeneración	4247
Total	70278

Tabla E.8: Potencia instalada de tecnologías convencionales (MW).

E.3.2 Datos empleados

En el desarrollo de este caso de estudio se han utilizado las series de producción históricas de las distintas tecnologías para el caso español, la demanda y los requerimientos de reservas secundaria y terciaria. Estos datos han sido obtenidos del sistema de información de Red Eléctrica (E-sios [34]). Las producciones históricas de energía eólica e hidráulica, el producible hidráulico y el nivel de los embalses han sido facilitados por personal de REE. El parque de generación ha sido cedido para la realización de este trabajo por DTU (Technical University of Denmark); estos datos fueron suministrados por Platts, Mc Graw Hill Financial [65], y han sido corregidos y ratificados con los informes anuales sobre la operación del sistema eléctrico REE [109].

Potencia instalada de tecnologías convencionales Se ha considerado en todo momento que el parque de generación actual está suficientemente dimensionado para una penetración de renovables del 40 % de energía eléctrica, con lo que no se ha considerado ninguna modificación. Sí se han tenido en cuenta los cierres programados de centrales previstos que no se han incluido en el modelo, tales como las centrales de carbón Teruel 3, La Pereda Hunosa, Escucha, Cercs, y el desmantelamiento de la central nuclear de Garoña. Tampoco se han tenido en cuenta aquellas centrales proyectadas cuya construcción ha sido paralizada. Las potencias instaladas de cada tecnología están recogidas en la tabla E.8 de elaboración propia a partir de los datos del parque de generación.

Rampas consideradas en las centrales convencionales En este trabajo se han considerado las rampas de subida y bajada de la producción de las centrales nucleares, ciclo combinado y carbón. En la tabla E.13 se presentan los valores de rampas asignados a las centrales nucleares. En el caso de las centrales de ciclo combinado, ante la ausencia de datos públicos, se ha realizado una aproximación. Considerando los valores de rampas proporcionados en el informe de Meibom et al. [53] se han asignado los valores más rápidos a las centrales construidas recientemente y los más lentos a las más antiguas. Estas centrales se han modelado de manera individual, considerando cada grupo de generación por separado. Con las centrales de carbón se han tomado las mismas consideraciones tomando los valores de rampa del informe de Meibom et al. [53] siguiendo un criterio idéntico. En este caso todas las centrales de carbón se han considerado de manera agregada por lo que los resultados de la restricción de rampa no son realistas. Esta aproximación está justificada puesto que en la práctica las centrales que están sometidas a restricciones de rampa de manera más severa son las centrales de ciclo combinado puesto que son las más rápidas, y por tanto las que responderán a las variaciones de la demanda.

Restricciones de potencia mínima Para las centrales de carbón y ciclo combinado se han obtenido de los informes del Ministry of Industry, Energy and Tourism, MINETUR [66, 67].

E.3.3 Escenarios considerados

En la tabla E.9 se presenta un cuadro resumen de las principales características de los escenarios. Las hipótesis planteadas en cada caso analizan el comportamiento del sistema eléctrico ante diversos valores de sus variables.

Nombre	Rampas nuclear	Precio combustible	Precio CO_2 (€/tn)	Escenario hidráulico	Precio sombra hidráulica (€/MWh)	Producción eólica	Producción renovable	Demanda
1-Base	Históricas	Medio	51	Medio	90	PANER	PANER	Base
2-Nuclear	Datos REE	Medio	51	Medio	90	PANER	PANER	Base
3-High fuel	Históricas	Alto	150	Medio	165	PANER	PANER	Base
4-Low fuel	Históricas	Bajo	26	Medio	70	PANER	PANER	Base
5-Dry	Históricas	Medio	51	Seco	95	Baja[5]	PANER	Base
6-Humid	Históricas	Medio	51	Húmedo	85	Alta[6]	PANER	Base
7-Low RW	Históricas	Medio	51	Medio	90	Media [7]	Baja [8]	Baja

Tabla E.9: Escenarios considerados

- Escenario 1, caso base que asume las hipótesis del PANER, así como una pluviosidad, precios de combustibles y emisiones de CO_2 medios.
- Escenario 2, a diferencia del anterior considera rampas más rápidas de aumento y disminución de la producción de las centrales nucleares. En este escenario se analiza cómo influiría una operación más flexible de las centrales nucleares existentes en los precios de la electricidad, en la energía renovable vertida y en el modo de operación de las centrales convencionales.
- Escenarios 3-4, donde se estudia la influencia de distintos escenarios de precios de combustibles y de precios de derechos de emisiones de CO_2 (altos y bajos).
- Escenarios 5-6, en los que se modelan distintos años meteorológicos (húmedo y seco), que tendrán influencia en la producción renovable (hidráulica y eólica), y por tanto en la operación de las centrales convencionales. En estos escenarios no se considera la producción eólica estimada por el PANER, sino que, partiendo de la hipótesis de que existe una correlación entre la pluviosidad y la ventosidad, se establecen distintos factores de capacidad [9], bajo para el escenario con menor disponibilidad de recurso eólico (escenario 5) y superior en caso contrario (escenario 6).
- Escenario 7, en este caso se plantea la posibilidad de que las previsiones del PANER en cuanto a instalación de renovables y demanda no se cumplan, teniendo en cuenta tanto la desviación actual respecto al plan, como otros efectos de la crisis económica en cuanto a la inversión en renovables y a la demanda esperada. Por tanto, se han calculado las producciones totales de cada tecnología.

A continuación pasaremos a detallar las características de cada caso y los resultados obtenidos. Las potencias instaladas y producciones anuales procedentes de fuentes renovables establecidas en el PANER están recogidas en la tabla E.10. Estas previsiones han servido como base para determinar las hipótesis de los distintos escenarios.

[9] El factor de capacidad se definirá en la ecuación (E.39).

	2016		2017		2018		2019		2020	
	MW	GWh	MW	GWh	MW	GWh	MW	GWh	MW	GWh
Hidráulica	22.109	37.566	22.169	38.537	22.229	38.443	22.289	38.505	22.362	39.593
<1 MW	256	760	259	765	262	743	265	819	268	803
1-10 MW	1.796	4.398	1.828	4.712	1.855	4.856	1.882	5.024	1.917	5.477
>10 MW	20.057	32.408	20.082	33.060	20.112	32.844	20.142	32.662	20.177	33.314
Bombeo	5.700	8.023	5.700	8.023	5.700	8.023	5.700	8.023	5.700	8.023
Solar	9.700	19.649	10.508	21.741	11.394	24.088	12.371	26.719	13.445	29.669
FV	6.319	10.565	6.760	11.345	7.246	12.222	7.780	13.208	8.367	14.316
CSP	3.381	9.084	3.747	10.397	4.149	11.866	4.592	13.511	5.079	15.353
Eólica	29.778	60.573	31.708	64.483	33.639	68.652	35.819	73.197	38.000	78.254
Onshore	29.278	59.598	30.708	62.238	32.139	64.925	33.569	67.619	35	70.502
Offshore	500	975	1.000	2.245	1.500	3.727	2.250	5.577	3.000	7.753
Biomasa	1.048	6.510	1.149	7.171	1.265	7.931	1.410	8.876	1.587	10.017
Sólida	810	5.066	887	5.545	972	6.074	1.073	6.699	1.187	7.400
Biogás	238	1.444	262	1.626	293	1.858	337	2.177	400	2.617
TOTAL	56.945	116.297	59.863	123.975	62.887	131.261	66.294	139.619	69.844	150.030
Cogeneración	335	2.014	359	2.160	385	2.317	403	2.428	423	2.551

Tabla E.10: Estimaciones del PANER para potencia instalada y producción de energías renovables.

1- Escenario "Base"

En este caso de referencia se han tenido en cuenta las previsiones establecidas en el PANER en cuanto a la energía generada con fuentes renovables: eólica, biomasa, fotovoltaica, termoeléctrica e hidráulica fluyente, que aparecen en la tabla E.10. Los valores de demanda también se han tomado de las previsiones del PANER. Como se ha mencionado en el apartado anterior, no se ha considerado la construcción de nuevas centrales convencionales.

Es complejo determinar el valor de las rampas puesto que los datos varían según las fuentes consultadas, Foro Nuclear [110] o Atienza [68], entre otras. Por ello, para el caso base se ha tomado como aproximación, una estimación basada en valores reales de la máxima rampa que ha tenido lugar en el sistema eléctrico español, en concreto, el 29 de marzo de 2013, entre las 13:30 y las 15:00h. Se han considerado idénticos valores para las rampas de subida y de bajada. La rampa obtenida ha sido de 0,2733 MW/min que se ha usado para todas las centrales nucleares, y también en los escenarios 3 a 7.

En lo que se refiere a los precios de los combustibles y de las emisiones de dióxido de carbono, se han aplicado precios medios, que se indican en las tablas E.11 y E.12 respectivamente.

Hipótesis	Carbón	Fueloil	Lignito	Gas Natural	Uranio
Low	4,14	11,27	3,40	8,76	1,57
Medium	4,30	11,61	3,84	8,77	1,62
High	5,06	12,00	3,99	9,33	2,86

Tabla E.11: Precios de los combustibles para los distintos escenarios (€/GJ).

Respecto al año meteorológico considerado se ha supuesto una tendencia media. Teniendo en cuenta esto, se han utilizado series históricas hidráulicas de años con un índice de producible hidráulico medio anual cercano a la unidad (0,82), eligiéndose como año de referencia el 2006. Para simular las exigencias de las confederaciones hidrográficas se han tomado como referencia los niveles de las reservas del año tipo, fijando el precio sombra de la energía hidráulica en función de la diferencia entre los niveles de embalse obtenidos en la simulación y los correspondientes en el tiempo del año de referencia. Para el caso base el precio sombra se ha fijado

Hipótesis	Precio (€/tn CO_2)
Low	26
Medium	51
High	150

Tabla E.12: Precios de las emisiones de dióxido de carbono para los distintos escenarios.

en 90 €/MWh.

2- Escenario "Nuclear"

En este caso se asumen las mismas hipótesis de precios, potencia instalada y pluviosidad que en el base, con la salvedad de que los valores de rampa de las centrales nucleares son distintos.

En el caso "Nuclear" se utilizan valores proporcionados por el antiguo director de REE en Atienza [68], donde se discuten las condiciones de operación flexible de las tecnologías nucleares. Pese a que en este informe se puede deducir un valor de rampa de 0,7569 MW/min [10], que confiere una mayor flexibilidad a las centrales nucleares que las registradas históricamente, y que en otros informes, encontrados en la web del foro nuclear, estos valores de rampa son aún más elevados, se han tomado en la mayor parte de los escenarios idénticos valores al del caso base, puesto que en la práctica esta supuesta flexibilidad no se aplica en la operación del sistema. Al igual que en el caso base, se han supuesto idénticos valores de rampa a subir y a bajar. Estos valores están recogidos en la tabla E.13.

Escenario/s	1, 3-7	2
Rampa (MW/min)	0,2733	0,7569

Tabla E.13: Valores de las rampas a subir y bajar de las centrales nucleares para los distintos escenarios.

[10] En este informe se afirma que las centrales nucleares españolas pueden presentar rampas de subida hasta la plena carga del orden de 12-24 horas. Teniendo en cuenta que potencia de las centrales oscila entre 460 y 1090 MW, se han supuesto estos valores para el cálculo de las rampas.

3- Escenario precio elevado de los combustibles: "High Fuel"

Además de suponer unos precios de los combustibles medios, como se ha establecido en los escenarios 1 y 2, se han tenido en cuenta distintos escenarios de precios futuros siguiendo las predicciones del Annual Energy Outlook (AEO) (Energy Information Administration [101]) para el lignito, carbón (hulla y antracita), fuel-oil y gas natural; y del International Monetary Fund [111] para los precios del uranio.

Aunque en la AEO se presentan cuatro escenarios de precios futuros: "Reference", "High growth", "Low growth" y "High price"; en este análisis sólo se han analizado tres, bajo ("low growth"), medio ("reference") y alto ("high price"). Puesto que los precios fijados por la AEO tienen carácter regional, con el objeto de obtener unos precios más acordes con la región de estudio, se han calculado las ratios de crecimiento de precio de la AEO con respecto a un año de referencia, 2011, y se han multiplicado estas ratios por los precios en el mercado español para el año de referencia. Estos precios de referencia se han obtenido de:

- Carbón. En el caso del carbón tanto antracita, como hulla, lignito negro y lignito pardo, se han tomado los precios de referencia de BOE [112], y los poderes caloríficos de cada tipo de carbón de Greenpeace [113].

- Gas natural. En CNE [114] se recogen los precios de las importaciones de gas natural.

- Uranio. Se han empleado los datos de una presentación de Iberdrola de junio de 2009, Molina Orero [115]. En los costes de combustible no están incluidos los costes de gestión de residuos.

- Fuel-oil. Se han utilizado las hipótesis establecidas en Wilmar para casos de estudio en otros países. En cualquier caso las centrales de fuel-oil no se utilizan actualmente en la generación española peninsular (sí se emplean en los sistemas insulares) y es previsible que no se utilicen en el futuro.

Los precios considerados para los combustibles están resumidos en la tabla E.11.

Otro factor determinante en la composición del mix energético asociado al uso de combustibles fósiles será el precio de los derechos de emisión de dióxido de carbono. La determinación del precio futuro de estas emisiones es muy compleja, debido a la alta volatilidad de los precios de emisiones en el pasado, tal y como puede apreciarse en la figura E.12, donde se han representado los precios históricos EUA, obtenidos de Sendeco [116]. El precio máximo del periodo fue de 28,3 €/tn, mientras que el mínimo se situó en 2,7 €/tn. Debido a esta alta volatilidad, se ha optado por suponer tres escenarios extremos de precios de derechos de emisiones de dióxido de carbono para estudiar la influencia en el mix de generación. Para ello se ha supuesto en primer lugar que en el año 2020, objeto del estudio, los precios del comercio de emisiones habrán aumentado considerablemente, tanto por la situación medioambiental como por el reiterado incumplimiento de Kyoto. Partiendo de este incremento se han establecidos tres escenarios con precios muy distintos que nos permitirán realizar un estudio diferenciado acerca de la influencia de este parámetro en la composición del mix de generación, tal y como se verá en los resultados. Los precios aplicados en cada uno de los supuestos, alto, medio y bajo, pueden encontrarse en la tabla E.12. Las hipótesis de precios de emisiones utilizadas en cada escenario están recogidas en la tabla E.9.

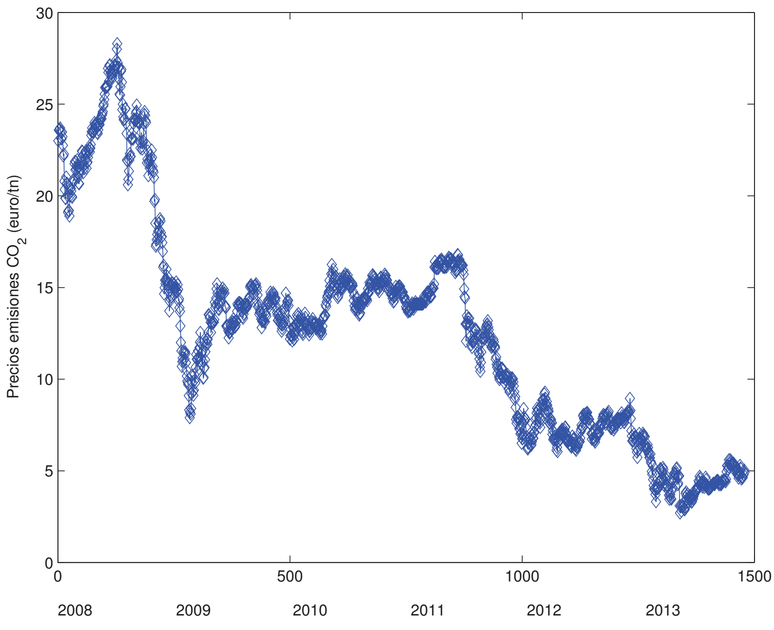


Figura E.12: Evolución de los precios EUA de los derechos de emisiones de CO_2 (enero 2008 - octubre 2013).

En resumen, en este escenario se considera la posibilidad de un panorama medioambiental adverso en el que por un lado, los combustibles fósiles hayan pasado su cénit de producción (“peak oil”), y su escasez eleve enormemente los precios. Además se considera un gran aumento de los derechos de emisión, ya sea debido a que cambie la regulación o a que el mercado refleje de manera más fidedigna el efecto pernicioso de estas emisiones, asignando un alto coste a las externalidades negativas de las emisiones responsables del efecto invernadero. La idea es determinar los costes de operación ante el escenario más adverso posible para las tecnologías convencionales, es decir, alto precio de combustible y de derechos de emisión. El escenario opuesto será planteado a continuación (escenario 4), en el que se planteará la opción más favorable para las tecnologías convencionales.

4- Escenario precio bajo de los combustibles: “Low Fuel”

En este caso se ha considerado una previsión de los precios de los combustibles fósiles más optimista, basada en las hipótesis de la AEO. De la misma manera, los precios de los derechos de emisión de dióxido de carbono son más bajos que en el escenario medio. Estos valores pueden consultarse en las tablas E.11 y E.12.

5- Escenario meteorológico seco: “Dry”

En el caso español, las precipitaciones no son homogéneas entre años consecutivos, antes al contrario, existe una gran variabilidad, por lo que los años se tipifican meteorológicamente como muy secos, secos, medios, húmedos y muy húmedos. Con el objeto de estudiar la influencia de la pluviosidad en la composición del mix de generación, se han establecido escenarios que reflejen esta variabilidad. A priori, este efecto debería ser significativo puesto que la energía hidráulica y especialmente los grandes embalses poseen una capacidad reguladora en el sistema eléctrico, debido a que son grandes almacenamientos de energía. Por tanto, en un año húmedo la variabilidad de la producción renovable podrá ser contrarrestada por la disponibilidad energética de los embalses hidroeléctricos. De lo contrario, en un año seco, esta regulación tendrá que llevarse a cabo por las centrales convencionales.

Estos distintos tipos de años hidráulicos tendrán influencia en la energía hidráulica disponible. Además de eso, se ha considerado que aquellos años con una alta pluviosidad son también más ventosos, y viceversa. Las borrascas, o zonas de baja presión, llevan asociadas tanto precipitaciones como vientos fuertes. Sirva como ejemplo lo ocurrido en el año 2010, en el que las precipitaciones fueron abundantes, y la ratio de energía eólica producida respecto a la capacidad instalada fue la más elevada de los años 2008 al 2010. Por todo lo anterior, se ha supuesto que la producción de energía eólica en el escenario húmedo tiene un factor de capacidad superior al establecido en el PANER, tomando en este escenario la ratio obtenida con los datos históricos de 2010, mientras que en el seco se ha supuesto un factor de capacidad menor. Por otro lado, aunque una mayor pluviosidad está lógicamente asociada a un descenso de la radiación solar recibida, esta interdependencia no ha sido tenida en cuenta, aunque tendría un efecto de disminución de la producción de las plantas termoeléctricas, principalmente, pues dependen de la radiación directa, pero también en las fotovoltaicas.

Para simular la regulación de las confederaciones españolas se han fijado los precios sombra de la energía hidráulica, que se han deducido siguiendo el razonamiento de la sección E.2.2. Estos precios tuvieron que ser ajustados tras realizar las simulaciones para validar la hipótesis de precio sombra de partida. Para ello, se han tomado como valores de referencia iniciales al comienzo de la simulación los niveles de embalsado del año meteorológico de referencia escogido en cada hipótesis, tal y como se resume en la tabla E.6. Una vez realizadas todas las simulaciones se ha corroborado que se han respetado los consumos hidráulicos, comprobando que los niveles de los embalses al final de la simulación son similares a los de referencia del año tipo. Los precios empleados en cada escenario están recogidos en la tabla E.9. Los resultados obtenidos están recogidos en la tabla E.14, donde se puede observar que en ningún caso las diferencias han sido superiores al 6 % respecto al año de referencia, por lo que se puede concluir que el uso de la energía hidráulica ha sido acorde con las especificaciones de regulación de las confederaciones.

Niveles embalses (GWh)	Base	Nuclear	High Fuel	Low Fuel	Dry	Humid	Low RW
Año referencia	7362	7362	7362	7362	6649	12298	7362
Simulación	7276	7256	6981	7214	6358	12036	7353
Diferencia (%)	-1,18	-1,45	-5,18	-2,01	-4,37	-2,12	-0,12

Tabla E.14: Niveles embalses (GWh) tras simulaciones.

6- Escenario meteorológico húmedo: "Humid"

En este caso se ha considerado un año meteorológico húmedo y un mayor índice de producción de energía eólica con respecto a la potencia instalada, tomando como base los datos del año 2010.

7- Escenario baja inversión en energías renovables: "Low RW"

En este escenario se han tratado de simular los efectos de la crisis económica en el cumplimiento del PANER. Para ello, se ha calculado la potencia instalada futura en el año 2020 de las distintas tecnologías renovables, teniendo en cuenta, por un lado, la desviación actual de las previsiones del PANER tomando como referencia las establecidas para el año 2012, y por otro los incrementos de potencia instalada en este año respecto al año 2011. Es además previsible que esas disminuciones en la inversión en renovables se acentúen si se tiene en consideración la ley de reforma del sector energético [11], que, previsiblemente, desincentivará, aún más, la inversión en renovables, lo que repercutirá en la potencia instalada. Si se atiende a las consideraciones del sector renovable podría parecer que el crecimiento en potencia instalada durante último año (2011-12) no podrá servir de base para cálculos futuros, pues se augura un crecimiento de la potencia instalada en los próximos años aún más ralentizado. No obstante, en este trabajo, se ha supuesto un crecimiento anual idéntico, porcentualmente, al experimentado entre los años 2011 y 2012, que ha sido de un 5,3 % para la energía eólica y de un 3,4 % para la fotovoltaica. En el caso de la potencia instalada de biomasa, se han supuesto las estimaciones del PANER ya que se han cumplido hasta el momento. Para la energía termoeléctrica, puesto que se ha desarrollado un modelo descrito en la sección E.2.1, se ha modelado la energía a partir de las radiaciones futuras, tomando como potencia instalada en 2020, la actual y la proyectada por Protermosolar [63] hasta la fecha. Puesto que se trata de una tecnología muy inmadura, los costes de inversión son muy elevados, y una regulación que no favorezca su instalación tendrá drásticas consecuencias en el aumento de la potencia instalada. Las potencias instaladas consideradas en este caso están resumidas en la tabla E.15.

El otro aspecto a tener en cuenta en el diseño de este escenario es la proyección de la demanda energética para el año 2020. Cuando se elaboró el PANER no se

[11] Ley 24/2013, de 26 de diciembre, del Sector Eléctrico.

Potencia instalada	PANER	Low RW	Variación
Eólica	38000	33576	-11,6
FV	8367	5470	-34,6
CSP	5069	2525	-50,2
Biomasa	1587	1587	0,0
Total	53023	43158	-18,6

Tabla E.15: Potencia instalada (MW) energías renovables en el escenario Low RW.

contempló que la crisis económica influiría en la demanda futura. Debido al decrecimiento del producto interior bruto, y puesto que la demanda está relacionada con el nivel de actividad económica, ésta ha disminuido en los últimos años. Sirva como ejemplo la demanda del año 2011 que descendió hasta alcanzar valores similares a los del año 2006. Para estimar la demanda futura, se han tenido en cuenta por un lado los datos del año 2012, tomando este valor como partida, y por otro las previsiones de crecimiento de la economía española proporcionados por International Monetary Fund [69] (IMF). Las previsiones de crecimiento de este organismo se limitan al año 2014, por lo que a partir de ese año se ha supuesto un escenario optimista de crecimiento constante del 0,4 % anual, idéntico al supuesto por el IMF entre 2013 y 2014. Los resultados de proyección de la demanda pueden consultarse en la tabla E.16. La diferencia entre la demanda del caso base y la de este escenario es de un 27,7 %.

E.3.4 Comparación de resultados

En este apartado se presentarán los resultados obtenidos en los distintos escenarios. Los parámetros analizados serán los precios del mercado diario, producción anual y factor de capacidad de las tecnologías, energía vertida, carga neta (definida como la demanda menos la producción renovable), variación de la carga neta, ratio de cobertura de renovables, variación horaria de la producción de energías convencionales, emisiones de dióxido de carbono y costes de operación.

Años	2012	2013	2014	2015	2016	2017	2018	2019	2020
Demanda (GWh)	252	248	244	245	246	248	251	255	260
Crecimiento económico (%)[a]	-1,4	-1,6	0	0,4	0,8	1,2	1,6	2	
Demanda PANER (GWh)	-	-	-	-	-	-	-	-	360
Variación demanda (%)	-	-	-	-	-	-	-	-	-27,7

[a]Datos tomados del informe International Monetary Fund [69]

Tabla E.16: Proyección de la demanda para el escenario Low RW.

Precios del mercado diario

Los precios del mercado diario (PMD) son una de las componentes esenciales del precio final de la energía. Estos precios son muy variables, pues dependen tanto de la demanda en cada momento como de la producción de renovables, que en algunos casos es muy variable, como en el caso de la energía eólica.

Los PMD se obtienen del valor marginal de la ecuación (E.2), restricción del mercado diario, obtenido tras la simulación, y representan los costes variables de la tecnología más cara incluida en la programación.

En la tabla E.17 se han analizado algunos parámetros estadísticos básicos de los PMD tales como la media, la mediana, la desviación típica y sus valores máximos y mínimos durante el periodo.

El PMD aumentará considerablemente para el año 2020 considerando el escenario base en el que su valor medio será de 89,15 €/MWh, un 54,3 % superior al del año 2012 (48,42 €/MWh). A la vista de los resultados puede afirmarse que el PMD dependerá fuertemente del precio de los combustibles fósiles, puesto que en el escenario de alto precio de los combustibles el precio medio es de 164,09 €/MWh mientras que si consideramos un precio de los combustibles bajo, este precio se sitúa en 70,43 €/MWh. Por tanto, ante un escenario de escasez de combustibles

PMD (€/MWh)	Base	Nuclear	High fuel	Low fuel	Dry	Humid	Low RW
Media	89,15	89,28	164,09	70,43	89,74	89,09	80,6
Mediana	90,79	90,79	165,44	72,39	90,79	91,15	89,03
Desviación típica	11,54	11,36	23,52	10,19	12,08	9,59	21,45
Mínimo	0	0	0	0	0	0	0
Máximo	121,48	121,28	243,4	97,99	126,13	120,42	117,5

Tabla E.17: Comparación precios mercado diario para distintos escenarios.

fósiles, este precio podría casi duplicarse respecto a un escenario base, al tiempo que se hace muy variable, tal y como se desprende del valor de su desviación típica (23,52 €/MWh), y de la diferencia entre su valor mínimo y máximo (0 y 243,4 €/MWh).

El tipo de año meteorológico influirá fundamentalmente en la variabilidad del PMD, puesto que los embalses pueden almacenar energía, que estará disponible para contrarrestar la variabilidad de las energías renovables. Podemos observar que en el escenario de mayor pluviosidad la desviación típica es menor que en el año más seco y que el valor máximo del PMD es menor.

En el caso de menor potencia instalada de energías renovables, E7, cabe señalar la alta variabilidad del PMD, esto se desprende, por un lado, del alto valor de la desviación típica, sólo comparable al escenario de alto precio de los combustibles fósiles, y, por otro, a la diferencia existente entre el valor medio y la mediana del PMD. Además, pese a que el valor medio del PMD es un 9,6 % inferior al del caso base, su valor máximo es tan sólo un 3,4 % inferior. En todos los casos se aprecia que el valor mínimo para el PMD es cero. Esto es debido a que con esa penetración de renovables habrá ciertas horas del año en las que toda la producción de energía provenga de fuentes renovables y de la energía nuclear.

Para analizar con mayor detalle el comportamiento del PMD, se han representado las monótonas de precios en la figura E.13, donde se aprecia que los precios tienen menos variabilidad en los escenarios 1, 2, 4, 5 y 6, y más en los escenarios de alto precio de combustible (E3) y baja penetración de renovables (E7). En este último, la gran dispersión del PMD es debida a que la potencia instalada de energías renovables con producciones con menor variabilidad (FV y CSP) es mucho menor que en los otros escenarios (-34,6 y -50,2 % respectivamente), mientras que en el caso de tecnologías con variación horaria más acentuada (eólica) la disminución de capacidad instalada es menor (-11,6 %).

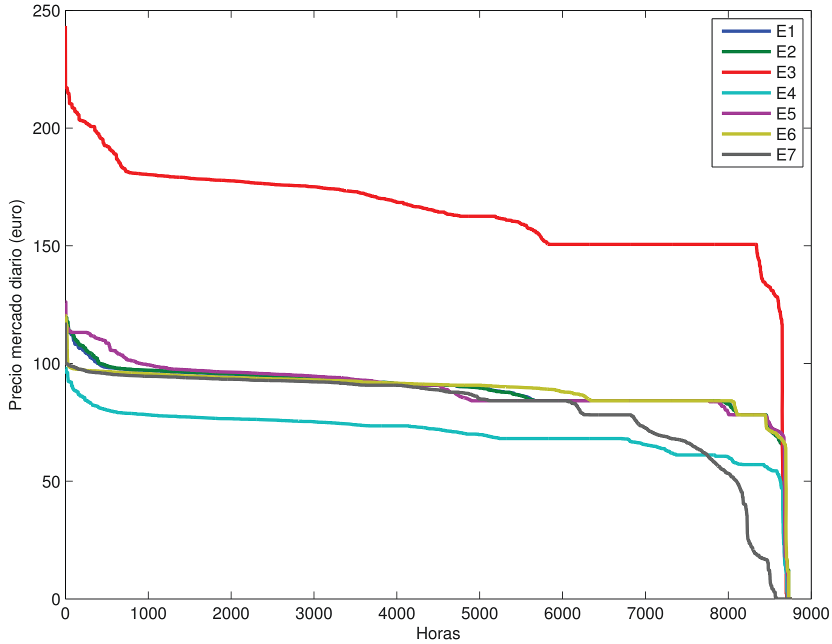
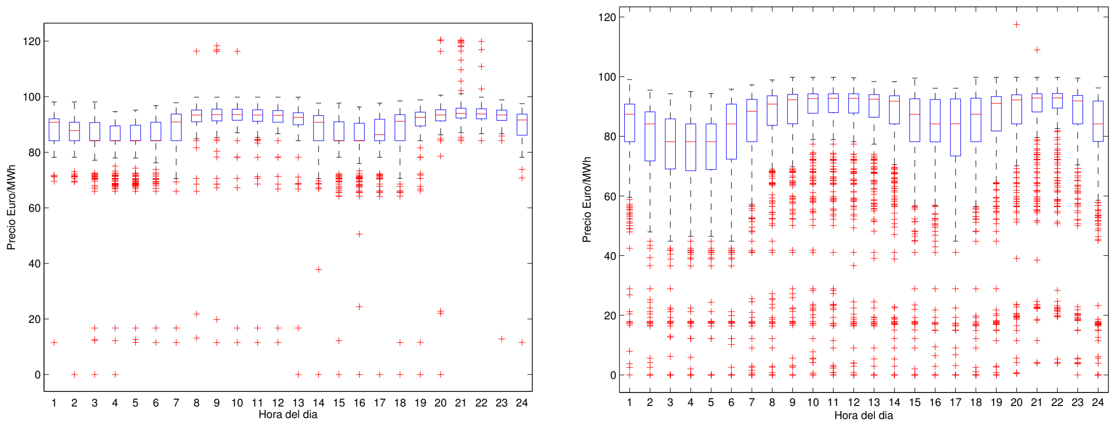


Figura E.13: Curva monótona de precios del mercado diario (€).

Para estudiar la variabilidad del PMD se han representado además los diagramas de cajas de los PMD horarios para el año de estudio en la figura E.14. Se han escogido tan sólo los escenarios con mayor y menor variabilidad con base en la desviación típica del PMD y a las monótonas de precios. Por tanto, en la figura E.14(1) se representan los precios del escenario con alta pluviosidad, 6, frente al escenario con menor penetración de renovables que aparece en la figura E.14(2). A la vista de los resultados puede concluirse que la variabilidad de los precios del escenario 7 es superior a la del escenario 6 que posee mayor capacidad de almacenamiento y más capacidad instalada de tecnologías renovables con menor variabilidad (FV y CSP). Esto se desprende de la mayor presencia de datos atípicos en el escenario 7, representados por las cruces rojas y de la mayor dispersión de los diagramas de caja (que recogen los datos situados entre los percentiles de 25 y 75 %). Otra de las cuestiones a señalar es que el precio es similar en ambos casos, pese a que en el escenario 7 la demanda es un 26,8 % menor. De esto último puede concluirse que ante un escenario con una capacidad instalada de energías renovables similar a la del escenario 6 y con los niveles de demanda del 7, el PMD podría reducirse considerablemente.



(1) Escenario Humid. (2) Escenario Low RW.

Figura E.14: Diagrama de cajas del PMD en cada hora del día.

Producción por tecnologías

En la figura E.15 se han comparado las producciones anuales de cada tecnología en el escenario base con los valores obtenidos en el año 2011. Como puede observarse los resultados son coherentes, pues las tecnologías convencionales hidráulica, carbón y nuclear han producido en términos generales una cantidad de energía similar a igual potencia instalada. El aumento de la demanda entre ambos años (105.000 GWh) ha sido suplido tanto por tecnologías renovables (FV, CSP, biomasa y eólica) como por centrales de gas natural (en esta producción están incluidos tanto los ciclos combinados como la cogeneración). La variación de la demanda entre los años 2011 y 2020 está representada en la figura E.16, donde aparece detallada por tecnologías.

En la figura E.17 están representadas las producciones anuales de cada tecnología, clasificadas por combustible, en el eje z. En el eje de abscisas se representan las tecnologías, mientras que en el de ordenadas los escenarios. Cabe destacar el

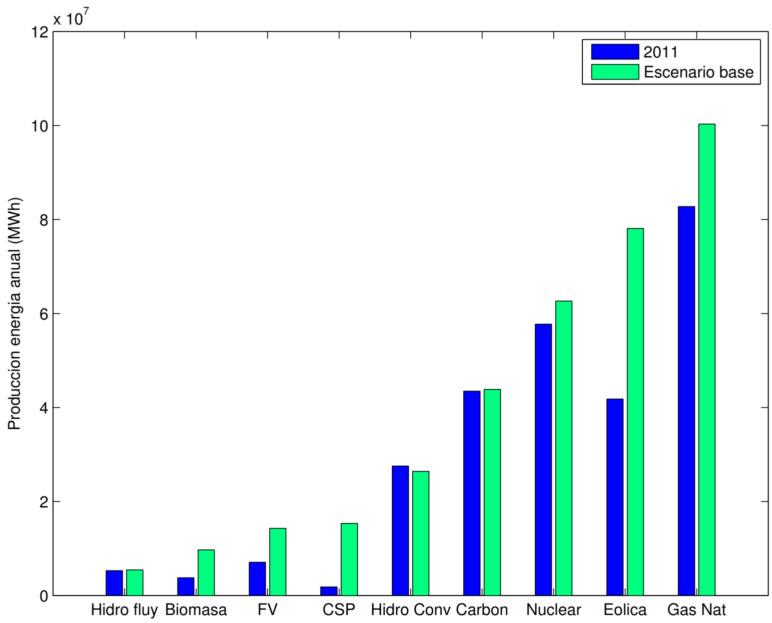


Figura E.15: Comparación entre producciones anuales del año 2011 y el caso base.

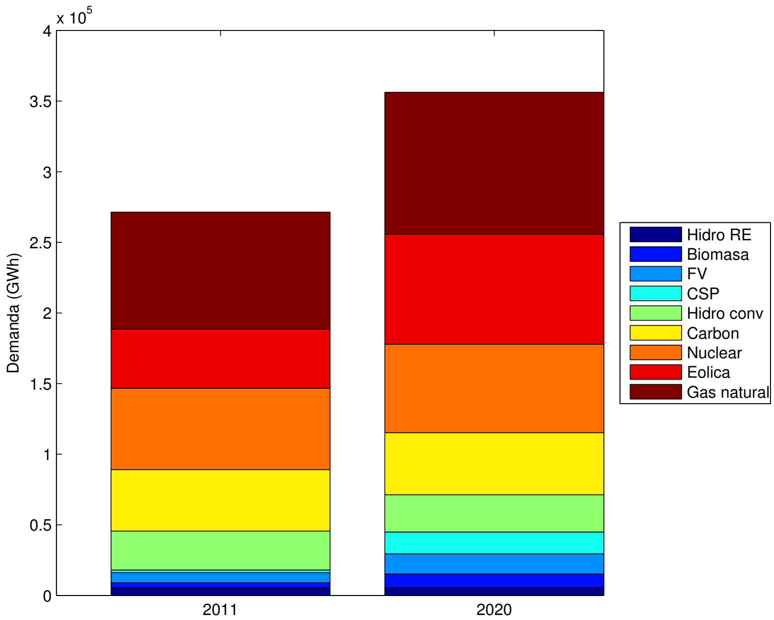


Figura E.16: Demanda de los años 2011 y 2020 (GWh) por tecnologías.

nivel de producción de la energía eólica, que para el escenario planteado por el PANER superaría la producción nuclear y de centrales térmicas de carbón en todos los escenarios excepto en el escenario 4, en el que por el contrario sería superior a la de las tecnologías basadas en gas natural y nuclear, pero no a las de carbón.

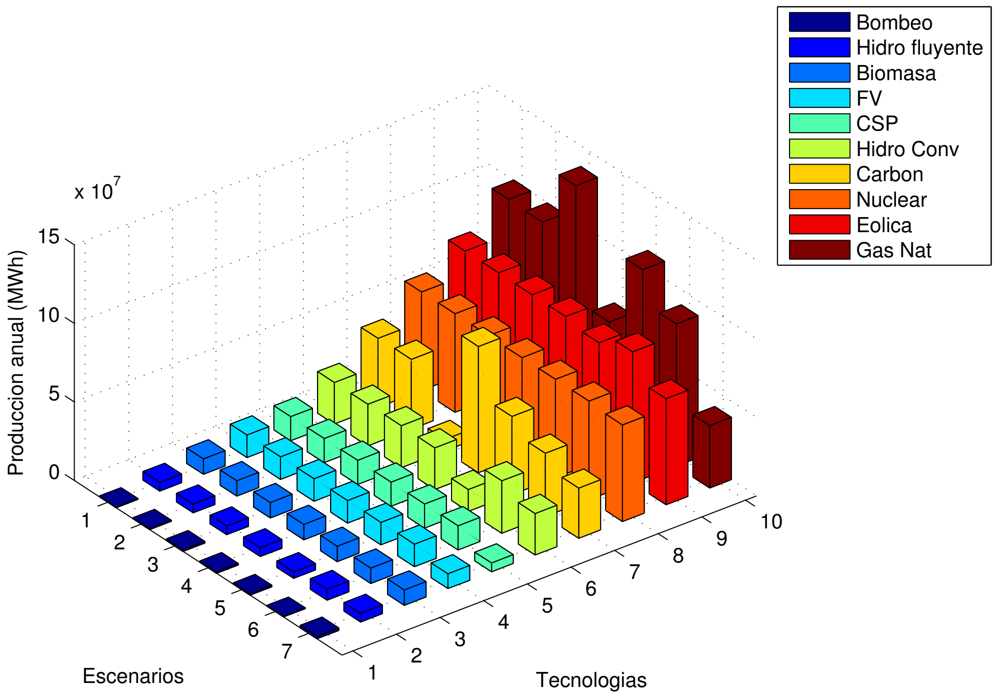


Figura E.17: Producción por tecnología para cada escenario (MWh).

Se observa también que el futuro precio de los combustibles y de los derechos de emisión puede condicionar la composición de la producción eléctrica. Comparando el escenario 3, con altos precios de los derechos de emisión y de combustibles con el 4, bajos precios, podemos concluir que en el primer caso las centrales de carbón verán mermada su producción anual debido a sus altas emisiones de dióxido de carbono, mientras que en el escenario 4 ven incrementada su producción debido al menor precio de su combustible.

Otro aspecto a destacar es la disminución de la producción de energía renovable del escenario 7, debido a la menor capacidad instalada. En este escenario, ante la disminución de la demanda la tecnología eólica superaría a la producción del resto de tecnologías. En la figura E.18 puede observarse la producción agregada de cada escenario.

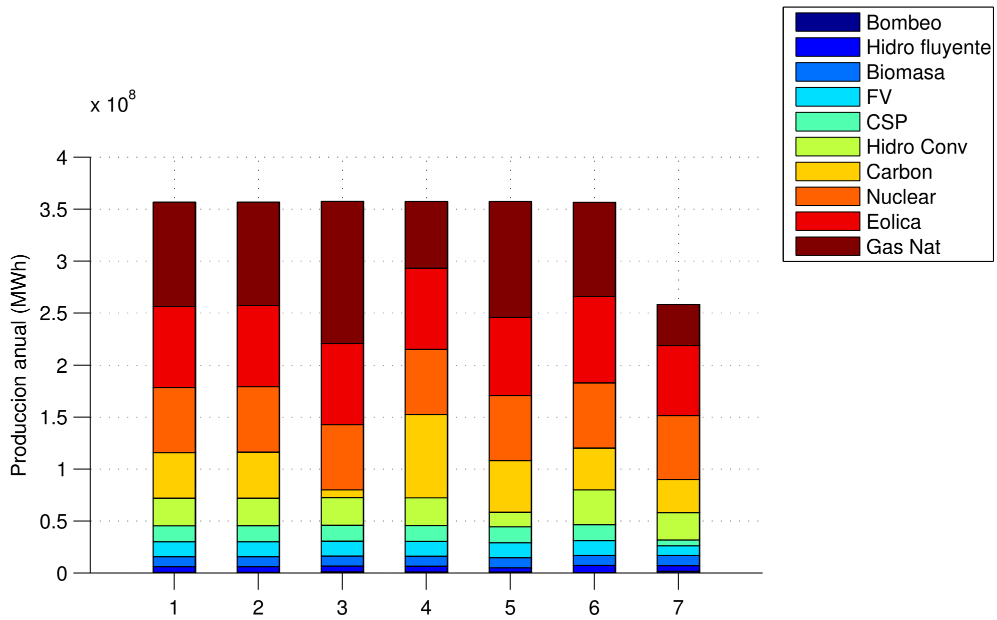


Figura E.18: Producción agregada por tecnología para cada escenario (MWh).

Factores de capacidad

El factor de capacidad se define como la ratio entre la producción de una tecnología durante un número de horas (n_h), y la energía que produciría si estuviese operando a su potencia nominal instalada (P_{inst}) durante el periodo considerado.

$$FC = \frac{\sum_{1}^{n_h} E}{n_h \, P_{inst}} \tag{E.39}$$

En la figura E.19 están representados los factores de capacidad de cada tecnología, clasificadas por combustibles, en los distintos escenarios. En el eje de abscisas están representadas las tecnologías, en el de ordenadas los distintos escenarios y en el eje z los factores de capacidad.

Puede observarse que para las tecnologías renovables FV, eólica y biomasa los factores de capacidad apenas varían entre los distintos escenarios. La hidráulica fluyente varía su producción, y por tanto, su factor de capacidad en función de las precipitaciones. En el caso de la termoeléctrica existe una diferencia entre los valores de FC de los escenarios 1 a 6 y el escenario 7 (Low RW). Aunque las series de producción se han obtenido del modelo de CSP implementado, para los escenarios

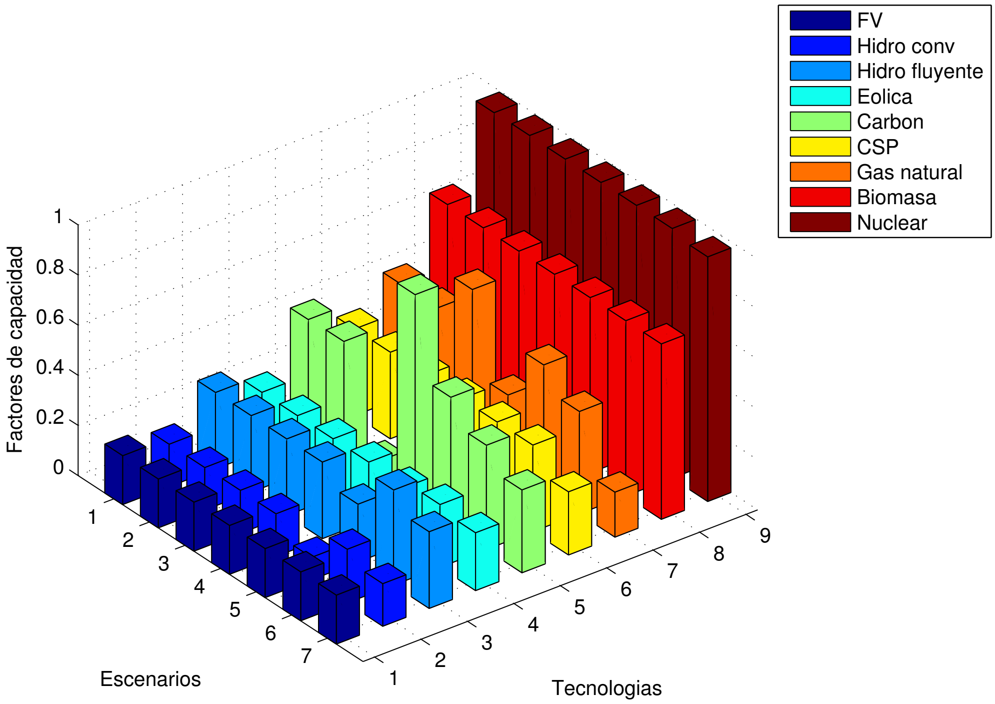


Figura E.19: Factores de capacidad de las tecnologías por escenarios.

1 a 6 se han tomado los valores de producción anual del PANER haciéndose un escalado; mientras que en el escenario 7 se han calculado las producciones a partir de las potencias instaladas en ese caso, que están resumidas en la tabla E.15. Por tanto, hay una pequeña variación entre los factores de capacidad aplicados en la elaboración del PANER, y los obtenidos en la elaboración de este modelo. Esta diferencia en el factor de capacidad podría ser debido a dos factores. Por un lado, en este modelo se han considerado datos de radiaciones históricas que han sido normalizadas y multiplicadas por la media de los últimos veintidós años. Esta normalización podría inducir a una infra-estimación de la radiación futura, ya que como establece Sanchez-Lorenzo et al. [117] las radiaciones directas en los últimos años han aumentado, y por tanto, la energía solar disponible considerada es inferior a la que habría en el año 2020. Por otro lado, es posible que en el PANER se hayan considerado mejoras en el rendimiento de las tecnologías termoeléctricas debido a la evolución de su curva de aprendizaje. En los próximos años esta tecnología alcanzará un mayor nivel de madurez por lo que es previsible que su rendimiento se incremente. Estas dos consideraciones redundarían en un incremento del factor

de capacidad de esta tecnología en el escenario 7.

De todas las tecnologías renovables, la que posee un mayor FC es la biomasa, puesto que la curva de producción considerada en este caso es constante a lo largo del tiempo. El factor de capacidad de la energía eólica se sitúa en torno al 0,23. Las tecnologías que dependen de la energía solar tienen FCs pequeños puesto que su producción está limitada a las horas de luz, en el caso de la FV (0,19), y su valor aumenta en la CSP debido al almacenamiento (0,34-0,29). La hidráulica fluyente tiene valores diferentes en función de la pluviosidad, que oscilan desde el 0,23 en el escenario seco, pasando por el 0,31 para un escenario medio y alcanzando un 0,38 para un año húmedo.

La tecnología nuclear tiene FC muy elevados (0,99), puesto que las lentas rampas de subida y bajada y los elevados costes de puesta en marcha y parada, hacen que opere de una manera poco flexible. Estos valores son muy elevados y superiores a los que se dan en la realidad, puesto que no se han considerado las indisponibilidades de la tecnología nuclear por las recargas de combustible ni otras paradas programadas. En el escenario 7, se observa una leve disminución (0,97) puesto que ante una demanda menor y una alta ratio de capacidad de tecnologías renovables instaladas (respecto a los niveles de demanda), esta energía ha de operar de manera más flexible por las altas cotas de producción renovable alcanzadas en relación con la demanda.

En el caso de la hidráulica convencional los FC dependen también de la pluviosidad, siendo del 0,14 para el año seco, 0,19 para el medio y 0,23 para el húmedo. En este caso los FC son pequeños puesto que el agua embalsada ha de utilizarse para usos distintos de la producción energética, y a que las programaciones interanuales del uso de agua de los embalses restringen el consumo debido a la incertidumbre meteorológica del siguiente año.

En el caso de las tecnologías basadas en carbón y en gas natural, puede observarse que los FC son complementarios entre sí, y que en aquellos escenarios en los que la tecnología que complementa la producción renovable es el carbón (E4), el FC de ésta es el más elevado (0,83), mientras que disminuye en las tecnologías de gas natural (0,29). Por el contrario, en un escenario con un valor elevado del precio de los derechos de emisión (E3), el FC del carbón disminuye (0,07), mientras que el de gas natural aumenta (0,62).

En la figura E.20 se representan los factores de capacidad acumulados de cada escenario.

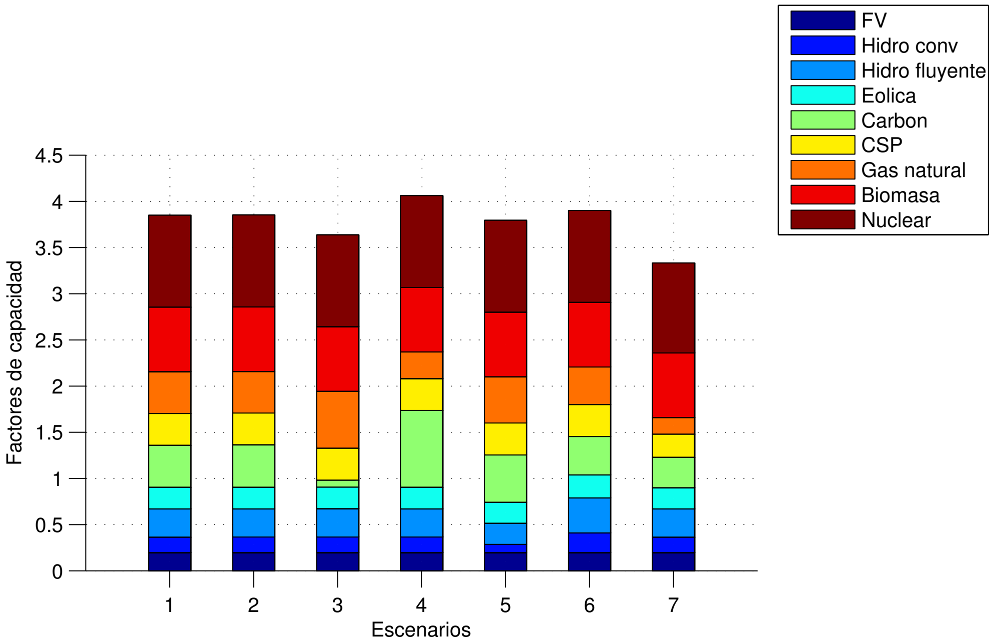


Figura E.20: Factores de capacidad agregados de cada escenario.

Energía eólica disponible y vertida

En este apartado se analiza qué proporción de la energía eólica producida está disponible para el sistema eléctrico teniendo en cuenta las restricciones de rampa de los generadores convencionales. Estos datos están resumidos en la tabla E.18, donde se presenta la producción eólica incluida en la programación horaria. También está cuantificada la energía vertida, es decir, aquella energía que es posible producir, porque existe recurso eólico suficiente para ello, pero que no ha podido ser integrada en la red al resolver las restricciones de la programación horaria. Esta energía vertida es debida fundamentalmente a las restricciones de rampa, puesto que es la restricción a la generación que limita la producción de renovables en el modelo empleado. No se ha tenido en cuenta, que será necesario incluir en la programación más unidades convencionales para proporcionar energía reactiva y respuestas de inercia.

Esta energía vertida obtiene su valor mínimo en el escenario con mayor pluviosidad, E6, debido a que la mayor disponibilidad de energía hidráulica permite

Eólica	Base	Nuclear	High fuel	Low fuel	Dry	Humid	Low RW
Potencia instalada (MW)	38000	38000	38000	38000	38000	38000	33576
Producción (GWh)	78089	78141	78068	78095	75302	83310	67482
Energía vertida (GWh)	107,2	55,1	128,1	100,3	79,3	1,7	302
% vertidos	0,137	0,070	0,164	0,128	0,105	0,002	0,446
Factor de capacidad	0,234	0,234	0,234	0,234	0,226	0,25	0,229

Tabla E.18: Energía eólica producida y vertida.

sustituir a las energías convencionales, y debido a su mayor versatilidad es posible responder a las variaciones de energía eólica. En la práctica, en el sistema español los años con mayor pluviosidad (2010 y 2012) han estado acompañados de los mayores vertidos de energía eólica, 315,2 y 121,1 GWh, respectivamente. Esto es debido a la correlación temporal entre la energía eólica e hidráulica, es decir, aquellas horas en las que es necesario vaciar los embalses al tiempo que existe disponibilidad de recurso eólico. Esta situación puede ocurrir en un área geográfica determinada mientras que no sucede en otra. Puesto que en este modelo se consideran los embalses de manera agregada no existe sensibilidad respecto a este tipo de situaciones, por lo que no están contempladas estas restricciones que producirían un aumento de la energía eólica vertida.

Comparando los escenarios base, E1, y nuclear, E2, podemos afirmar que unas centrales nucleares con una operación más flexible mejorarán la integración de la energía eólica en la red. En ese sentido, también se puede afirmar que el uso de tecnologías más rápidas en el mix de generación como los ciclos combinados, escenario High Fuel, E3, ha de reducir los vertidos de viento, respecto a un mix con centrales más lentas, escenario Low Fuel, E4. En este caso esto no sucede por la forma en la que el modelo trata estas centrales, pues en el caso de ciclos combinados se han modelado de manera individual, es decir, el modelo trata las centrales una a una con sus respectivas rampas de subida y bajada, mientras que en el caso de las centrales de carbón, son tratadas de manera agregada con lo que la restricción de rampa se aplica a la central agregada, y por tanto, el modelo no tiene sensibilidad ante las restricciones en la variación de potencia. Por tanto, con un modelo más realista la energía vertida en el escenario 4 sería mayor que la del escenario 3.

La cantidad de energía vertida alcanza su máximo valor en el escenario Low RW, E7, con un aumento de casi un 300 % respecto al escenario base. En este escenario la cobertura de la demanda por parte de fuentes renovables es del 46 % mientras que en el escenario base es de un 40 %. Por tanto, el incremento de energía vertida es debido a una mayor cobertura de la demanda por tecnologías renovables y a la menor capacidad fotovoltaica y la termoeléctrica, que poseen una menor variabilidad que la energía eólica.

AEE [118] recoge los datos de energía eólica vertida de los últimos años (2008-2012). Estos vertidos son debidos a limitaciones por huecos de tensión (actualmente casi despreciables), limitaciones en la red de distribución (14,2 GWh en 2012), en la red de transporte (13,9 GWh en 2012) y excedentes de generación (93 GWh en 2012, 19,3 GWh en 2011 y 202,2 GWh en 2010). En los resultados de la simulación tan sólo se calculan los vertidos debido a la última causa, excedentes de generación. A la vista de estos resultados puede concluirse que la energía eólica vertida obtenida en el modelo es acorde a los datos históricos.

Carga neta

La carga neta se define como la demanda eléctrica menos la producción renovable efectiva, es decir, descontando los vertidos de energía. La figura E.21 muestra las monótonas de la carga neta para los distintos escenarios.

En general, puede afirmarse que la carga neta es muy variable a lo largo del año, debido por un lado a las variaciones de demanda entre las horas valle y punta, y a la coincidencia de estas horas con momentos de alta y baja producción de energía procedente de fuentes renovables. Los valores oscilan entre los 1200 y los 55000 MW.

Se observa en el escenario 7 (Low RW), que al disminuir la demanda, la carga neta también lo hace, puesto que aunque disminuya la potencia instalada de tecnologías renovables en términos relativos aumenta la ratio de generación renovable *versus* demanda (46 %) con respecto al resto de escenarios (40 % en el escenario base). También se aprecia como en los escenarios seco (E5) y húmedo (E6) la carga neta es ligeramente superior e inferior respectivamente, puesto que se han supuesto valores inferiores y superiores a la media, respectivamente, de producción eólica e hidráulica. En el resto de los escenarios 1 a 4, la curva de carga neta es idéntica y aparecen superpuestas unas a otras, adquiriendo valores intermedios con respecto a los escenarios seco y húmedo.

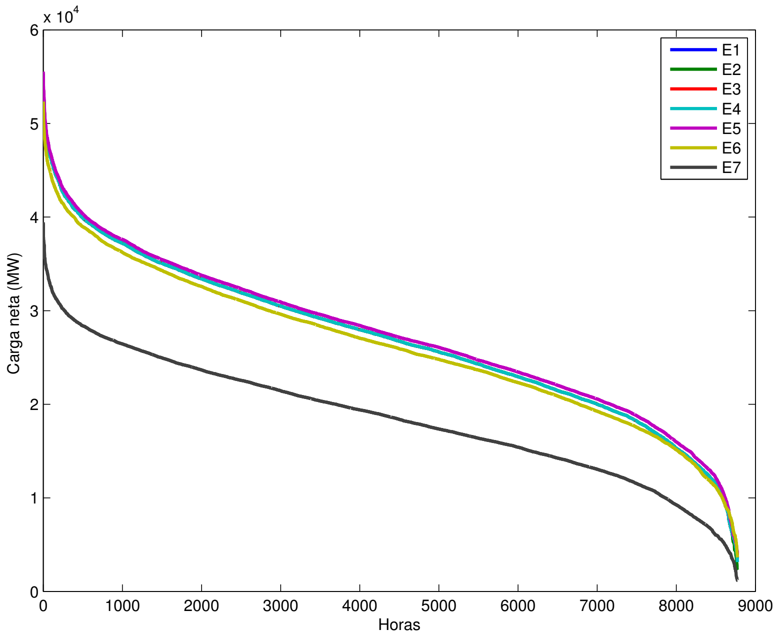


Figura E.21: Monótona de la carga neta.

Otro aspecto a tener en cuenta es la capacidad del parque de generación convencional de gestionar la demanda teniendo en cuenta variabilidad de las energías renovables. Para ello se ha representado la variación de la carga neta entre dos horas consecutivas en la figura E.22. Esto nos da una idea de los cambios de producción de energías renovables y su coincidencia con la demanda, y por tanto, cómo han de operar las centrales convencionales ante esos cambios de demanda neta, o demanda que han de cubrir las centrales convencionales respecto a la hora anterior. Se observa que la variación de la carga neta aumenta con la potencia renovable instalada, es inferior en el escenario Low RW (E7) que en el resto. Por tanto, a medida que aumente la capacidad renovable instalada será necesaria una cartera de centrales convencionales más flexibles.

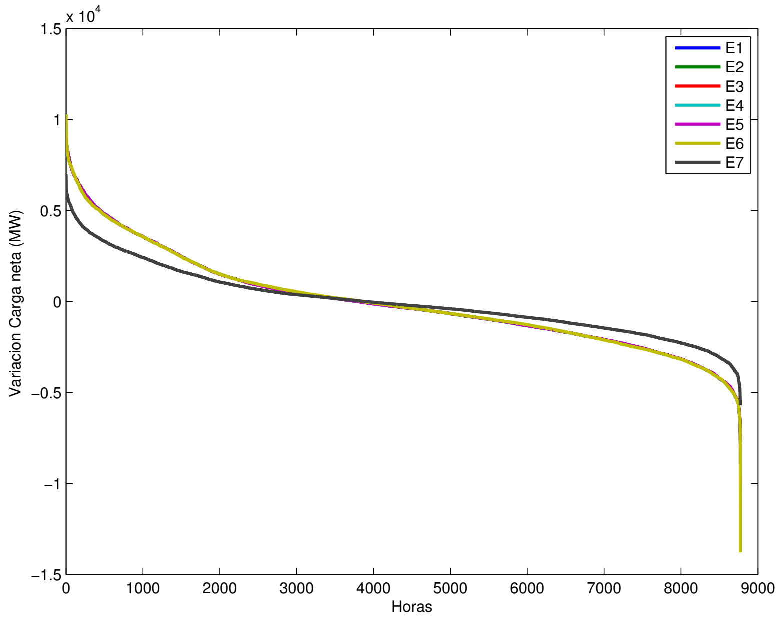


Figura E.22: Monótona de la variación de la carga neta.

Ratio de cobertura de la demanda

En la figura E.23 se ha representado la curva monótona de la ratio de cobertura de la demanda por parte de las tecnologías renovables. Tal y como era esperable se observa que la producción de energía por parte de las energías renovables no coincide con la demanda, pues la variabilidad de la cobertura es muy elevada. En el escenario Low RW, E7, donde se da una mayor ratio de capacidad renovable instalada respecto a la demanda, la ratio de cobertura es superior y la curva es más suave, además se da el máximo valor de ratio de cobertura que alcanza el 95 %. En el escenario con menor producción renovable por efecto de la baja pluviosidad, E5, la ratio de cobertura es la menor de todos los escenarios. Mientras bajo condiciones meteorológicas más favorables, escenario Humid (E6), las ratios son ligeramente superiores.

Estas ratios de cobertura no incluyen las restricciones debidas a requerimientos técnicos que se consideren en la conexión a red, por lo que el valor efectivo sería menor. En el año 2012 la máxima ratio de cobertura de la demanda por parte de

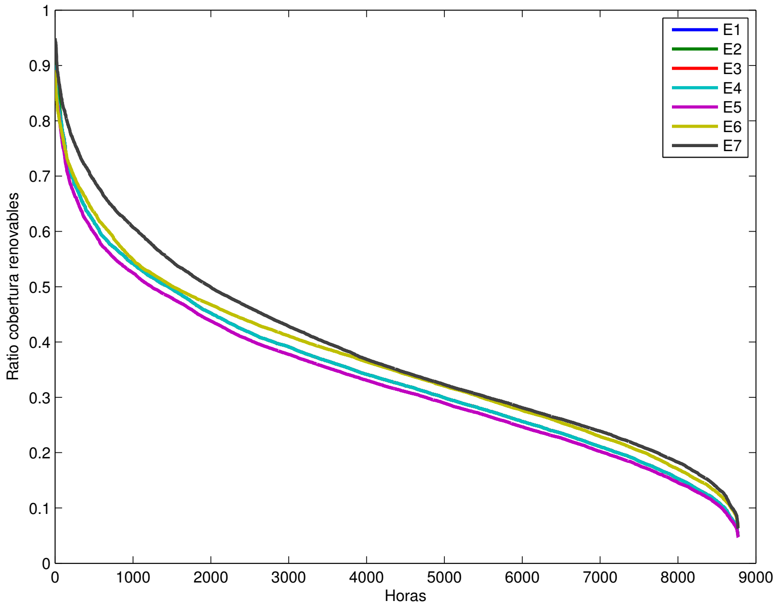


Figura E.23: Monótona de la ratio de cobertura de la demanda por parte de las tecnologías renovables.

la energía eólica fue del 64 % el 24 de septiembre a las 3:03h (REE [109]). Aunque este valor va aumentando año tras año sería necesario realizar estudios en más profundidad que contemplaran restricciones de red para determinar cuál será el máximo valor efectivo alcanzable.

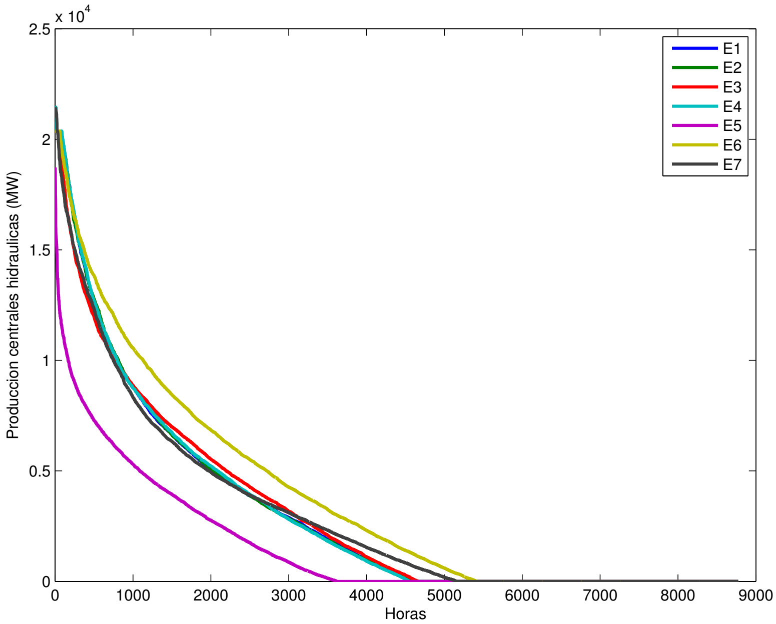
Variación horaria de la producción de tecnologías no renovables

Una vez evaluada la variación de la producción por parte de fuentes renovables, pasamos a evaluar cómo influye esta variabilidad en las centrales convencionales. Se ha analizado la variación de la producción entre horas consecutivas para las centrales hidráulicas, de carbón y gas natural.

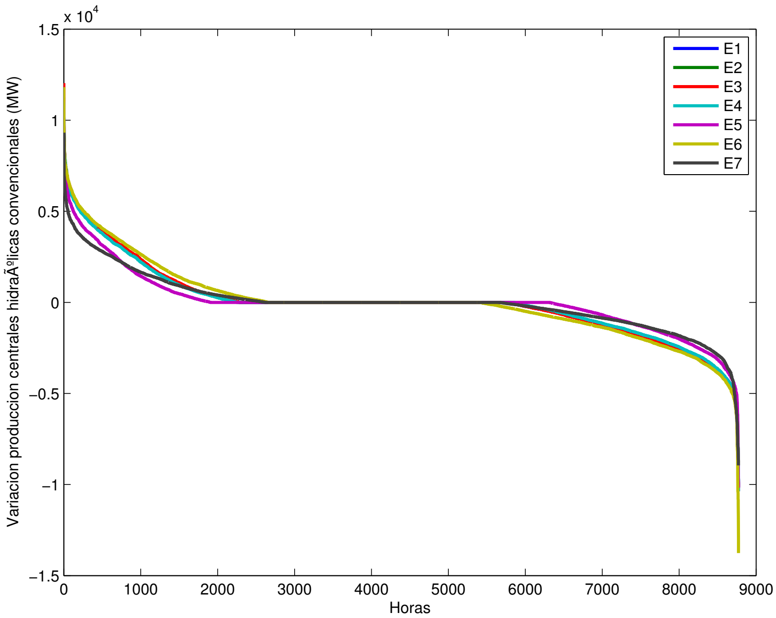
En la figura E.24 se han representado tanto las monótonas de la producción anual de energía hidráulica, figura E.24(1), como la variación de esta producción, figura E.24(2). Se observa que estas tecnologías no operan durante todas las horas del año, lo que concuerda con sus bajos factores de capacidad. Sus horas de operación oscilan entre las 3600 (E5) y las 5400 (E6) dependiendo del escenario. Fijándonos en esto, observamos que la parte central de la monótona de variación (valor igual a cero) coincide en su mayor parte con el número de horas en las que las centrales no están en funcionamiento. Observando los extremos de la curva podemos apreciar que la variación, exceptuando algunos valores atípicos extremos, oscila entre 7500 MW para valores positivos y -5000 MW para negativos. Por tanto, su modo de funcionamiento es muy flexible, ya que se utilizan para compensar las variaciones de producción de las energías renovables.

De manera análoga, en la figura E.25 se representa la variación horaria del parque de generación de tecnologías con gas natural, mostrándose tanto las monótonas de producción horaria E.25(1), como las variaciones de la potencia horaria E.25(2). A diferencia de las centrales hidráulicas, estas tecnologías funcionan de manera menos flexible. Sus horas de operación oscilan entre las 6800 (E7), 7900 (E4) y las 8700 (E3). En consecuencia, las horas consecutivas sin variación de potencia son unas 4000 al año. La variación de potencia en el resto de horas, excluyendo los 100 valores más extremos a subir y a bajar, oscilan entre un valor de 2.800 MW para valores positivos y -2.500 MW para negativos. Las variaciones extremas de producción de gas natural pueden alcanzar los 7000 MW, y coinciden con las puntas de demanda, donde se presentan oscilaciones de esta magnitud en la energía requerida. Del análisis del escenario Low RW (E7) se desprende que el número de puestas en marcha y paradas de estas tecnologías es elevado, debido a que el número de horas en las que todas las centrales están apagadas es unas 2000.

Por último, se representan en la figura E.26 las variaciones horarias de potencia de las centrales de carbón, mostrándose tanto la monótona de la producción anual, figura E.26(1), como la variación de la producción entre horas consecutivas para la cartera de generación, figura E.26(2). A diferencia de las tecnologías anteriores las centrales de carbón están conectadas la totalidad del año, a excepción del escenario 3, donde su producción se mantiene al mínimo durante un número elevado de horas (4500) y apagadas unas 1000 horas debido al alto coste de los derechos de emisión de CO_2. Como ya se había adelantado se corrobora en el escenario 4 que el bajo coste de combustible hace que se use predominantemente esta tecnología. En cuanto a la variación de la producción se observa en la figura E.26(2) que es mucho menor que en las tecnologías anteriores, alcanzando valores de unos 2200 MW para variaciones positivas y unos -2000 MW para las negativas. Se puede concluir que su modo de operación es el menos flexible de las tecnologías estudiadas en este apartado.

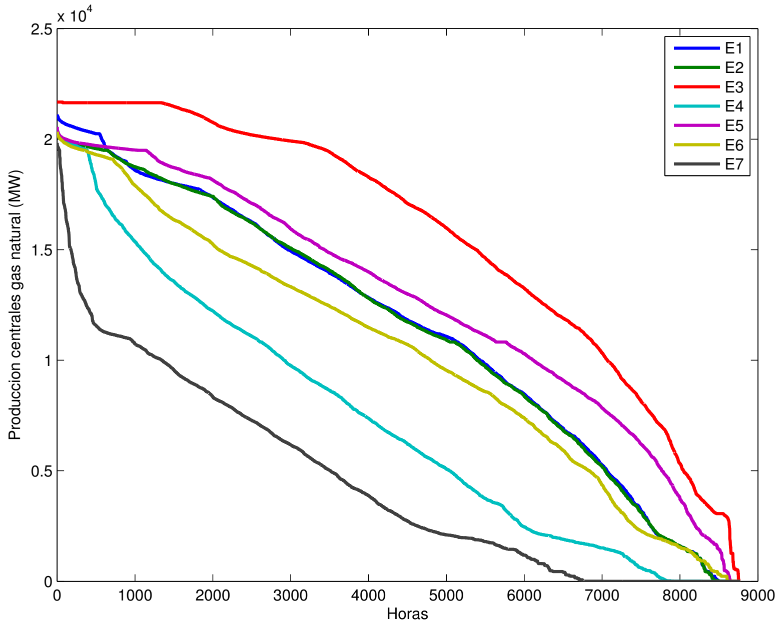


(1) Monótona de producción.

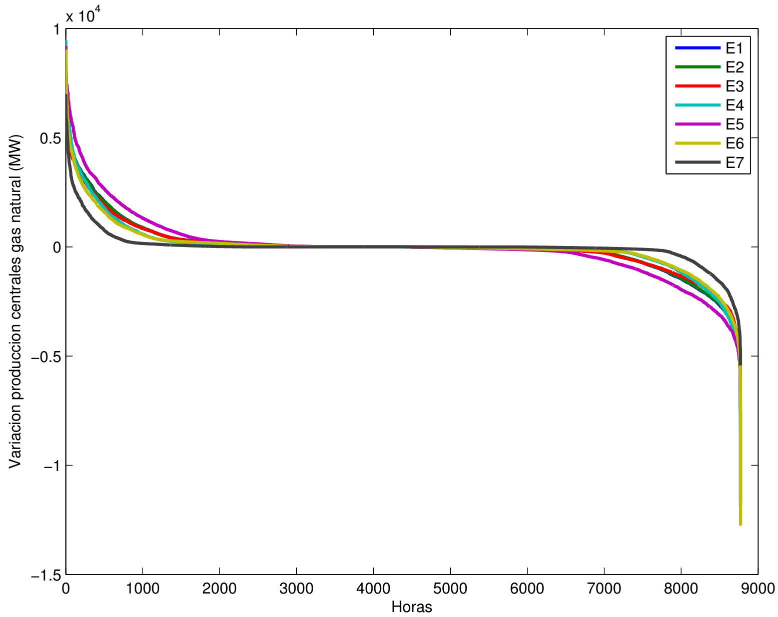


(2) Variación horaria de la producción.

Figura E.24: Análisis de la variación de la producción hidráulica convencional.

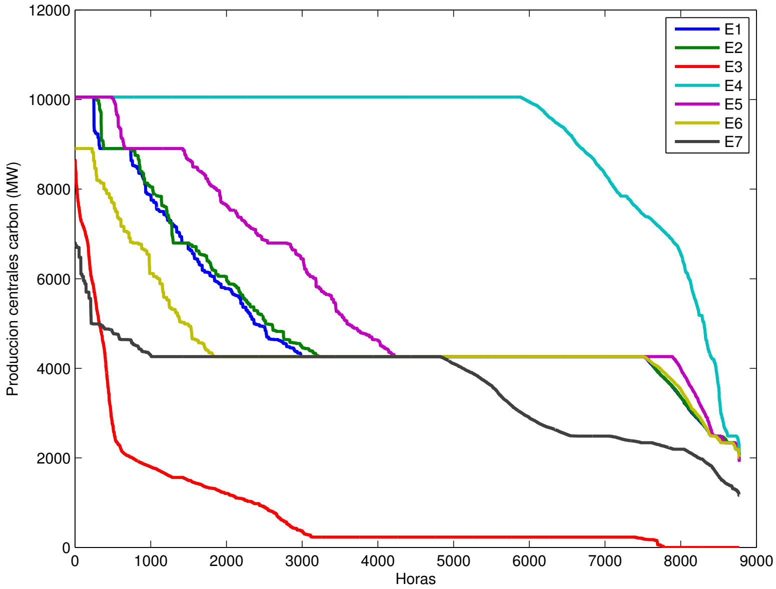


(1) Monótona de producción.

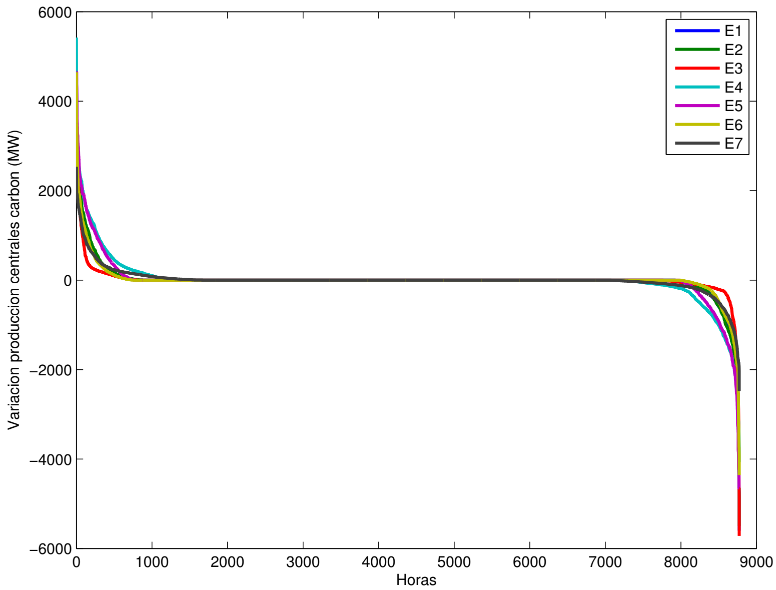


(2) Variación horaria de la producción.

Figura E.25: Análisis de la variación de la producción de las centrales de gas natural.



(1) Monótona de producción.



(2) Variación horaria de la producción.

Figura E.26: Variación horaria de la producción de las centrales de carbón.

Emisiones de dióxido de carbono

En la tabla E.19 están representadas las emisiones de CO_2 resultantes de cada escenario de generación. Los escenarios con mayores niveles de emisión serán el de baja pluviosidad (E5), seguido del de menores precios de los combustibles y derechos de emisión (E4). Por el contrario, el escenario con menores emisiones será el E7 por la disminución del nivel de demanda eléctrica, seguido del escenario con alta pluviosidad (E6).

Parámetro	Base	Nuclear	High Fuel	Low fuel	Dry	Humid	Low RW
Emisiones CO_2 (Mtn)	110	110	103	120	124	99	56

Tabla E.19: Emisiones CO_2 de cada escenario.

El protocolo de Kyoto establece un límite de emisiones en la generación de 83,3 Mtn EEA [119], que sólo se cumpliría en el escenario 7, ante un descenso de la demanda.

Costes de operación

En la tabla E.20 se presentan los costes de operación totales y desglosados para cada escenario que incluyen tanto los costes de emisiones de dióxido de carbono como los costes de combustible, durante la operación y el arranque.

A la vista de los resultados, se observa que ante un escenario de altos precios de combustibles y de derechos de emisiones los costes serán muy elevados comparados con los del escenario de referencia. Se observa también que una mayor pluviosidad disminuye los costes de operación, debido a la disponibilidad y al uso más extendido de las centrales hidráulicas convencionales. También se aprecia que en el caso de un descenso considerable de la demanda respecto al escenario base, Low RW, los costes de operación disminuyen sustancialmente debido a que la energía suministrada por tecnologías que usan combustibles es mucho menor (por la disminución de la demanda total).

Costes	Base	Nuclear	High Fuel	Low fuel	Dry	Humid	Low RW
Emisiones CO_2 (M€)	5587	5589	15427	3113	6266	5051	2853
CO_2 arranque (M€)	26	25	65	15	56	22	17
Combustible (M€)	8442	8429	10420	7731	9291	7742	4573
Combustible arranque (M€)	45	45	40	53	33	40	33
Operación (M€)	14100	14088	25952	10912	15647	12856	7475

Tabla E.20: Costes operación (M€).

E.3.5 Conclusiones

Tras el estudio realizado pueden extraerse las siguientes conclusiones:

- En los análisis realizados el precio del mercado diario medio aumenta considerablemente en el año 2020 en todos los escenarios propuestos, siendo el incremento mínimo del 38,9 % y el máximo de un 223,6 %. Esta variación se debe fundamentalmente al aumento de los precios de los combustibles. Además, la variabilidad del precio depende del porcentaje de generación renovable respecto a la demanda, siendo más variable en términos relativos (variación respecto a precio medio) en el escenario con mayor ratio de generación renovable *versus* demanda, “Low RW”.

- En un escenario con un precio muy elevado de los derechos de emisión de dióxido de carbono los ciclos combinados desplazan a las centrales de carbón. Estas últimas pasan a tener una débil presencia en el mix de generación.

- Los factores de capacidad de las centrales convencionales basadas en combustibles fósiles dependen tanto del precio de los combustibles como de los derechos de emisiones. En el caso de las centrales de ciclo combinado su factor de capacidad disminuye si los precios de emisión son bajos y el precio del gas natural aumenta.

- Los factores de capacidad de la energía hidráulica convencional y, por tanto, su producción dependen fuertemente de la pluviosidad del año meteorológico, variando desde 0,14 hasta 0,23 en los casos considerados.

- Una operación de las centrales nucleares más flexible, que incluya una respuesta a las variaciones de producción por un aumento de la generación de origen renovable, podría disminuir los vertidos de energía eólica un 51,4 %. En los casos estudiados se ha visto que la mayor parte de la energía eólica vertida es debida a las restricciones de rampa de las centrales nucleares, es decir, que en la operación habitual apenas se varía la potencia suministrada por estas tecnologías.

- El escenario con menor carga neta, es decir, menos energía de origen convencional, Low RW, tiene un mayor porcentaje de energía eólica vertida, con un aumento de casi un 300 % respecto al escenario base. En el escenario Low RW la cobertura de la demanda por parte de energías de origen renovable es del 46 % mientras que en el escenario base es de un 40 %. Por tanto, una mayor cobertura de la demanda por tecnologías de origen renovable tendrá como consecuencia un aumento de la energía eólica vertida.

- Las tecnologías convencionales (hidráulica, gas natural y carbón) operarán más frecuentemente a carga parcial ante un aumento de la capacidad renovable, puesto que la potencia horaria suministrada varía sustancialmente a lo largo del año.

- La variación de la potencia convencional suministrada hora a hora es más acentuada en el escenario Low RW que en el resto de los escenarios. Además la ratio de energía renovable *versus* demanda es superior, por lo que las centrales convencionales operarán de manera más flexible ante una mayor penetración de energías renovables, incurriendo en rampas severas en su funcionamiento.

- En este modelo, de entre las tecnologías no renovables, las centrales hidráulicas convencionales responden habitualmente a las variaciones de la demanda. Esto es debido a que estas centrales son las más rápidas (mayores rampas) y las de menores costes marginales. Además son las centrales convencionales con menos horas de operación anuales.

- Los ciclos combinados estarán sometidos a grandes variaciones de la producción entre horas sucesivas y aumentarán las paradas, por lo que operarán de manera más flexible. El pico agregado de variación de potencia más elevado es de 7.000 MW, que tiene lugar en los momentos de paso de horas valle de demanda a horas punta. En el escenario con mayor penetración de renovables disminuirán las horas de operación de estas centrales. En la misma línea, en este escenario tienen lugar menores fluctuaciones en la producción.

- Las centrales de carbón funcionan con una producción más estable que las de ciclo combinado e hidráulica convencional, operarán durante más horas al año experimentando menores fluctuaciones de potencia entre horas consecutivas.

- En el escenario con altos costes de derechos de emisión se invierte el funcionamiento de las centrales de carbón y las de ciclo combinado. En este caso las últimas pasarán a operar como centrales de base funcionando todas las horas del año y experimentando menores fluctuaciones en la producción, mientras que las de carbón experimentarán el efecto contrario, disminuyendo sus horas de operación e incrementando sus variaciones horarias.

- Ante un nivel de demanda igual al pronosticado en el PANER, con una cobertura renovable anual de un 40 % de la demanda no se cumpliría el protocolo de Kyoto respecto a las emisiones, ni siquiera en el escenario más favorable de mayor recurso hidráulico disponible. Sólo en el caso de que la demanda experimentase un pequeño incremento respecto a los valores actuales (2012) se cumpliría el protocolo de Kyoto en un escenario en el que las fuentes renovables proporcionasen el 45 % de la demanda.

- En un escenario con altos precios de derechos de emisión de dióxido de carbono los costes de operación se dispararían.

- Una mayor disponibilidad de recurso hidráulico repercutirá en una disminución de los costes de operación, tanto de las emisiones como de combustible. Por el contrario se incrementarán los costes de arranque.

- En el escenario con mayor cobertura de la demanda por parte de energías renovables junto con una demanda inferior, Low RW, los costes de operación disminuirán. Por el contrario los costes de combustible en el arranque aumentarán de manera relativa con respecto a los costes de combustible totales.